A MULTI-OBJECTIVE WELL PLACEMENT APPROACH WITH NPV AND REGIONAL PRESSURE BALANCE

BY

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To my beloved, helpful and supportive family, friends, and colleagues.
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THESIS ABSTRACT

Full Name: Menhal Abdulbaqi Al-Ismael

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Well placement optimization in large scale field development and water flooding projects becomes more challenging when considering more than one attribute for indicating the level of performance. Environmental effects and profitability are two important concerns in any field development. They help in evaluating the performance of sweeping hydrocarbon in the reservoir. Voidage Replacement Ratio (VRR) and reservoir pressure can both be used to assess regularity and environmental impact since they are the main subsurface contributors in the reservoir that might cause subsidence. On the other hand, Net Present Value (NPV) is used by investors to measure the cash flow profitability profile to help in conducting feasibility studies. In addition to well placement, well rate optimization is also important for achieving the desired objectives.

Previous work has been done by considering both VRR and NPV attributes in well placement optimization. That kind of study focuses on the value of VRR of the overall field. However, such technique might mislead the development to undesirable consequences since the resultant VRR might not consider unbalanced distribution of reservoir pressure. Significant positive changes in one area of the field might be opposed by significant negative changes in another area. This will result in severe alteration of the voidage replacement distribution that could not be represented properly by the total value of field VRR. In such cases, field VRR is not efficient for detecting these disparate regional changes. This study is assessing overcoming such cases by maintaining the environmental regularity attributes for predefined regions in the field. The process monitors each region and makes sure that all constrains are satisfied. Moreover, this study maintains the reservoir regional pressure during well location optimization instead of maintaining the VRR. Pressure reflects better measure of subsurface stability when evaluating the reservoir

environmental effects. Various cases for well placement optimization are evaluated and presented in this work.

ملخص الرسالة

الاسم الكامل: منهال عبد الباقي آل إسماعيل

عنوان الرسالة: تطبيق تعدد الهدف في تحديد مواقع حفر الآبار بوزن صافي القيمة الحالية والضغط الإقليمي

التخصص: هندسة البترول

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تزداد التحديات في تحديد مواقع واحداثيات حفر آبار النفط في مشاريع التطوير والانتاج وحقن الآبار مع ازدياد متغيرات تحديد مستوى الجودة والأداء. وتُعد الآثار الاقتصادية والبيئية من أهم عوامل نجاح مشاريع تطوير الحقول النفطية. حيث أن هذه العوامل تساعد في تقييم أداء عملية استخراج النفط من المكمن النفطي. وتتم دراسة هذه العوامل بأساليب مختلفة كمعدل الإفراغ والإحلال أو الضغط الداخلي للمكمن لتقييم الآثار البيئية حيث أن هذه الأساليب تساعد في تحديد مواقع حدوث هبوط سطحي. من ناحية أخرى، يتم استخدام صافي القيمة الحالية من قبل المستثمرين لحساب الأرباح والتدفق النقدي للمساعدة في إجراء دراسات الجدوى.

هنالك دراسات سابقة في مجال تطوير أساليب تحديد مواقع حفر الآبار تمت باستخدام صافي القيمة الحالية ومعدل الإفراغ والإحلال. تلك الدراسات ركزت على معدل الإفراغ والإحلال في كامل المكمن النفطي والتي قد تضلل المشروع التنموي إلى عواقب غير مرغوب فيها حيث أن معدل الإفراغ والإحلال الناتج قد لا يشير إلى التوزيع الغير متوازن للضغط في المكمن. قد تتعارض تغييرات إيجابية كبيرة في إقليم معين من المكمن مع تغييرات سلبية كبيرة في إقليم آخر. وهذا يؤدي إلى تغيير شديد في التوزيع الإقليمي لمعدل الإفراغ والإحلال والتي لا يمكن تمثيلها بشكل صحيح في القيمة الكلية لمعدل الإفراغ والإحلال للمكمن النفطي. ففي هذه الحالة لا يعتبر معدل الإفراغ والإحلال وسيلة فعالة للكشف عن هذه التغييرات الإقليمية المتباينة.

ولحل وتلافي السلبيات والمعوقات في الأبحاث السابقة فإن هذا البحث قد درس طريقة للحفاظ على اتزان الآثار البيئية في أقاليم محددة من المكمن. هذه الدراسة قامت بمراقبة الضغط الإقليمي والتأكد من الوصول لنتائج وفق جميع القيود البيئية والاقتصادية. علاوة على ذلك، تؤكد هذه الدراسة على أن الضغط الإقليمي هو مقياس أفضل من معدل الإفراغ والإحلال في تقييم الآثار البيئية في مشاريع الإنتاج النفطية. قامت هذه

الدراسة باستخدام عدة أمثلة افتراضية لإثبات جدوى هذه الطريقة، وقد تم ذكر جميع التفاصيل والنتائج والتي تبين كيفية استفادة المستثمرين من هذه الطريقة في تخطي التحديات الملازمة للتخطيط وتنمية وتطوير الحقول النفطية.

CHAPTER 1: INTRODUCTION

1.1 Introduction

Hydrocarbon field development and increment phases involve determining the number and locations of the production and injection wells within the field boundaries. Sometimes the development follows certain type of well patterns configuration which depends on reservoir geometries and locations. For example, for a reservoir with simple properties, such as a high permeability reservoir, only few wells might be needed since a single well may produce oil from a very large volume around the wellbore. As the complexity of the reservoir geometry increases, well location determination becomes more significant especially for heterogeneous reservoirs. The number of wells needed will be definitely increased in such cases. At the same time, the number of wells should be minimized to avoid extra costs without affecting oil production volume. So, there has to be some techniques to be followed to balance between the profit and cost. Too much time is spent by reservoir management engineers to come up with the best wells locations that provide an operation lined up with the preset constrains. The process involves complex workflow starting form reservoir geological studies up to reservoir simulation. Well location determination accuracy plays a major role in the reservoir productivity and health throughout the reservoir life. Therefore, a lot of effort is exerted on this significant stage which affects all subsequent development and production phases.

Since the relationship between engineering and geological variables affecting reservoir performance is not simple, determination of optimal well locations cannot be based on intuitive judgment. Therefore, there should be a process that helps in optimizing well location. The word "optimization" may be defined as the process of adjusting the inputs to a device, mathematical process, or experiment in order to find the minimum or maximum output of result. Optimization generally refers to the selection of a best element, with regard to some criteria, from some set of available alternatives. This criterion is defined by the objectives or constraints of interest. Therefore, an objective well-placement optimization tool is used to define the best well locations when considering one objective such as the Net Present Value (NPV). However, sometimes one parameter is not enough as an objective for certain problems. Unconstrained objective optimization ignores other important parameters. If NPV is considered alone as the objective of the well location optimization problem, other parameters such as environmental effects will not be considered, and hence getting unsuccessful results. Many decision making problems need to consider several constraints such as minimizing risk, maximizing reliability, minimizing deviation from certain limits, and minimizing cost. The main goal of the unconstrained objective optimization is to reach the best solution which corresponds to the minimum or maximum value of a single objective function. This type of optimization usually cannot provide a set of alternative solutions with different importance of constraints than others. However, the constrained or multi-objective optimization approaches do not provide single optimal solution. Having all the objectives and constraints in the problem, the optimization will result in an equation of weighted objectives and constraints in which an importance of each objective can be controlled. This is known as non-dominated, non-inferior, trade-off, or Pareto-optimal solutions. Therefore, a wider range of alternative solutions is achieved when a constrained optimization methodology is used. Also, the results can be easily tuned by compromising the importance of each constraint depending on the nature of problem and the desired results.

CHAPTER 2: LITERATURE SURVEY

2.1 Optimization

The word optimization may be defined as the process of adjusting the inputs to a device, mathematical process, or experiment in order to find the minimum or maximum output or result. Optimization generally refers to the selection of a best element, with regard to some criteria, from some set of available alternatives. This criterion is defined by the objectives of interest. Various approaches have been proposed for production optimization. Beckner and Song (1995) applied the traveling salesman framework on well placement problem using Simulated Annealing (SA) to find the optimum locations of the wells. Bittencourt (1994) used the polytope algorithm to optimize the scheduling of a field. Bittencourt et al (1997) hybridized Genetic Algorithms (GA) with the polytope algorithm and tabu search. They named this hybrid optimization technique the Hybrid Genetic Algorithm (HGA). Hybrid Genetic Algorithm was observed to improve the economic forecasts and CPU effort during optimization. Pan and Horne (1998) used kriging as a proxy to the reservoir simulator to decrease the number of simulations. Guyaguler et al. (2000) showed that when a Hybrid Genetic Algorithm is coupled with a kriging proxy, the number of simulations required for optimizing injectors well locations is decreased. Yeten et al. (2002) coupled GA with hill-climbing methods and an Artificial Neural Network (ANN) proxy to optimize the type, location and trajectory of nonconventional wells. Guyaguler and Horne (2001) assessed the uncertainty of the well placement results using utility theory, together with multiple realizations of the reservoir.

2.2 Well Placement Optimization

Today's market demands require intensive effort to find solutions approaching better profits and reduction in costly delays. Restrictive regulations and standards are also some of the various challenges facing industry from the oil and gas sector. Well placement optimization in large scale field development and water flooding projects becomes more challenging when considering profits, costly delays, and restrictive regulations as attributes for indicating the level of performance. The relationship between engineering and geologic variables affecting reservoir performance is not simple, and hence the determination of optimal well locations cannot be based on intuitive judgment. Many studies have shed the light on the importance of the well placement optimization and many techniques have been approached. In 2003, some studies presented an approach where an optimization technique based on a quality map in combination with genetic and polytope algorithms were used in determining optimal well locations. The quality map represents the production and injection effects in the reservoir in a two-dimensional map. The quality map approach in well placement optimization was first introduced by da Cruz et al. (1999). The map provides a measure of the production and injection quality within the reservoir. The advantage of the quality map approach is small computational effort and few simulation runs are needed, and hence consuming less CPU consumption time. On the other hand, the quality map approach works well in optimizing locations of wells all with the same completion intervals within the same layer in the reservoir which is not the case in the real world where well trajectories are often complicated and penetrating several layers. Moreover, this approach optimizes a single well type at a time and hence, either producers or injectors quality can be optimized.

Another approach proposed hybrid optimization technique based on the genetic algorithm with helper functions based on the polytope and the kriging algorithms. Genetic algorithm is a search experience-based technique for problem solving. This kind of algorithms is used to speed up the process of reaching a reasonable solution through intuitive judgment in order to ease the reasoning and making decisions. This algorithm combines the filtered solutions of the best among the solution vectors with random vectors. Thus, genetic algorithms modify the solution vectors instead of modifying a single point. In many problems, genetic algorithms may tend to converge towards local optima or even arbitrary points rather than converging towards the global optimum of the problem.

Similarly, greedy algorithms do not guarantee finding global optimum solutions. They basically look for the optimal solution in the neighborhood of the current solution. Therefore, global optimal solution might be reached for single optimum or smooth problems. It might also be useful in single objective problems since one optimal solution might be possible to define.

2.3 Well Rate Optimization

One important production well control parameter in interest is the well rate. Optimization of well rates involves allocating rates to individual wells. Many wells sometimes produce at rates which appear to be optimum, but they are actually limited by unnecessary restrictions to flow. All components of the well system have to be analyzed though modeling techniques to measure and evaluate the well performance and ensure that well rates are optimum. Nodal analysis is commonly used for this purpose as it analyzes the well starting at the reservoir average pressure up to the surface facilities.

In real world and in sophisticated reservoir and conditions, the selection of individual well rates becomes challenging. Moreover, operating under a set of physical system constraints and some engineering preferences increases the level of challenge in defining an optimization system to achieve the optimal well configuration with well rates that honor system and engineering constraints. Several studies considered optimizing well rates through different algorithms. Nondeterministic polynomial time (NP) approaches have been used through integer linear programming. One example of such approach proposed a new rate allocation optimization framework which can solve a problem given prioritized list of targets and limits as constraints. Sometimes it is not possible to satisfy all the system constraints in the same time. In such cases, prioritization approach would be the practical solution for reaching reasonable solutions.

Several optimization efforts focused on optimizing well locations by specifying the operating rates for the specified reservoir operational life time. When different well rates need to be specified, different approaches will be needed. A two-stage well placement optimization method has been developed based on adjoint gradient attempting to enable different specification of well rates. This methodology allows configuring well rates at an initial stage, and then estimates the optimal well rates at a second stage.

2.4 Reservoir Surveillance

An ongoing task during the lifetime of the reservoir is monitoring the reservoir and maintaining its performance. A lot of data is collected during production in intelligent fields (I-Fields) through well instruments. Permanent downhole gauges are installed at wellbores to measure different kind of information. Downhole under the surface in I-Field oil and gas wells, gauges measure important parameters for monitoring the health and the status of the reservoir in real-time basis. Each gauge is responsible for measuring certain property to determine the status of the well. These gauges are responsible for measuring temperature, pressure, oil rate and water rate. Also, some gauges are placed at the top of the well to determine the properties of the oil and the gas on the surface. Then, the data collected from these gauges are sent to different servers to be analyzed. Some applications are then used to reduce and to filter the real-time data coming from the wells. These kinds of applications enable visualizing the real-time data which help in describing the behavior of the well during a certain period of time. Surveillance applications use some kind of filters to deal with noisy data. Wavelet algorithm is used to remove the noises and reduce the number of relevant points. There are some additional steps done by these systems to handle data acquisition, storage and retrieval of the data in order to properly fit the needs.

Permanent downhole gauges are placed in the wells downholes for the sake of reservoir surveillance and to get what is happening in real time. The interest in permanent downhole gauges data goes beyond the knowing rates, pressure and temperature at any given time. The combination of the well production, when known, and pressure data is a good candidate for analyses and for real time rate allocation.

Well testing analysis is part of reservoir surveillance. Information obtained from flow and pressure transient tests are important for determining the productive capacity of a reservoir. Pressure transient analysis also provides estimates of the average reservoir pressure. There has to be sufficient information about the condition and characteristics of reservoir and well to adequately analyze reservoir performance and to forecast future production under various modes of operation. In general, well testing analysis is performed to evaluate well condition and reservoir characterization.

CHAPTER 3: THEORETICAL FOUNDATION

3.1 Net Present Value (NPV) and Environmental Effects

In practice, the intention is to place the wells in the locations most likely to achieve the highest NPV, as an objective. So, NPV is calculated during the planning and reviewed by investors to measure the cash flow profitability profile to help in conducting feasibility studies. NPV is a standard method for appraising long-term projects in which discount rates are considered to estimate a price as an output very close to the actual cost. The discount rate here accounts for the rate of return gained from the financial market investment. So, each cash flow C_t is discounted back to its present value (PV) which is calculated by dividing the net cash flow by $(1+d)^t$. Basically, PV is calculated as follows:

$$PV = \frac{C_t}{(1+d)^t} \tag{1}$$

where,

C_t = Cash flow

d = Discount rate

t = Time of the cash flow

Then, the NPV of a number of periods N is calculated by summing the present values for all the periods. Below is the formula for calculating NPV:

$$NPV = \sum_{t=0}^{N} \frac{C_t}{(1+d)^t} \tag{2}$$

where,

N = Number of periods

Another objective for optimizing well locations is the impact of field development activities on the environment. This is usually measured by using Voidage Replacement Ratio (VRR) value which refers to replacing the volume of oil, gas and water produced from the reservoir by injected fluids. VRR is an important parameter in planning and managing improve oil recovery (IOR) projects. VRR is calculated by dividing the injected fluid volumes by the produced fluid volumes. Basically, VRR calculation formula is as follows:

$$VRR = \frac{V_{inj}}{V_{prod}} \tag{3}$$

where,

V_{inj} = Volume of injected fluid

V_{prod} = Volume of produced fluid

Both V_{inj} and V_{prod} are calculated at reservoir conditions. So, at the primary recovery process, the value VRR is zero since there is no fluid injection. For VRR grater zero, fluid injection process has taken place. As VRR is increasing and approaching the value of one, the volume of externally injected fluid is increasing or the volume of produced fluid is decreasing which might mean the reservoir is being depleted.

Reservoir depletion increases the stress carried by the load-bearing grain framework of the reservoir rock. Consequently, this causes deformation effects such as grain-contact spreading, micro-crack growth and closure, cement breakage and grain rotation and sliding. Rocks then usually get compacted and as a result, its porosity gets reduced. Numerous reservoir deformation and subsidence incidents due to reservoir depletion have been reported. An example of such incidents is the Goose Creek oil field located in Baytown, Texas. After production of several million barrels of oil in the Goose Creek, bay water began to flood the oil field. Subsidence of more than 3 feet was reported due to extensive extraction of oil, water, gas, and sand from beneath the affected area. Other examples are the Lost Hills and Belridge oil fields located in San Joaquin Valley, California. Subsidence was measured from space using interferometric analysis of Synthetic Aperture Radar (SAR). After eight months of analysis, a subsidence of more than 200 mm was reported.

3.2 Reservoir Average Pressure

As mentioned earlier, environmental effects can be measured by VRR which is the ratio of reservoir barrels of injected fluid to reservoir barrels of produced fluid. This ratio is used by regulatory and environmental agencies to measure the impact of field development activities on the environment.[1] Injection rates should be controlled to be low enough to prevent over-pressuring which might induce unwanted fractures in the formation. However, these rates must also be high enough to make this costly process of fluid injection profitable. The damage introduced by over-pressuring could impact the environment negatively and might not be observed using VRR since the ratio can still be close to one. This work uses reservoir average pressure instead of VRR to maintain the formation health which impacts the environment during waterflooding process. Pressure data is the most valuable and useful data in reservoir engineering. It is included in all the phases of reservoir engineering calculations.

Therefore, NPV and reservoir average pressure are both obviously important in well locations optimization problem. Thus, a constrained optimization approach is used to take into account the profit and environment preservation. In other words, unlike the conventional optimization approaches that maximize only NPV, the new optimization approach is not only maximizing NPV, but also maintaining the environment by mainly controlling the reservoir average pressure.

3.3 Optimization Tool

3.3.1 Differential Evolution

Differential evolution (DE) is an efficient and powerful technique for solving optimization problems over continuous space. It is a population-based parallel direct search method which has been widely applied in many scientific and engineering fields. It optimizes a problem by improving a candidate solution iteratively by maintaining specific measure of quality. Such methods are called metaheuristics since only few or no assumptions are made about the problem and can search very large dimensional spaces of candidate solutions. However, metaheuristics such as DE do not assurance an optimal solution is ever found. DE technique is good for multi-dimensional optimization problems. DE optimizes a problem by maintaining a population of candidate solutions. Then, new candidate solutions are created by combining existing candidates, and then it keeps the best candidate solution according to the optimization problem criteria.

DE algorithm works by having a set of candidate solutions (which are called agents) initialized randomly within the search space. By using simple mathematical formula, these agents are moved around the search space by combining the positions of existing agents from the population. If this movement causes an improvement, the new position is accepted. The algorithm continues trying to reach good solution. To optimize a function Φ with M real parameters, DE is initialized with a random population of N_p agents. These agents $\vec{x}_j$, $j \in \{1,2,\ldots,N_p\}$ are generated in the interval $[\vec{x}_L, \vec{x}_U]$, where $\vec{x}_L$ and $\vec{x}_U$ are the lower and upper limits of the agents. The DE consists of three main procedures, which are mutation, recombination, and selection. These three main procedures are repeated until the desired criteria is reached. The DE iterates through the following steps in order to reach the best candidate solution.

Initialization	For each parameter vector $\vec{x}_j^{\kappa}$, randomly select three other vectors $\vec{x}_{r_1}^{\kappa}$, $\vec{x}_{r_2}^{\kappa}$ and $\vec{x}_{r_3}^{\kappa}$ from the population. The four vectors indices j, r_1, r_2, and r_3 must be distinct. κ is the iteration number.
Mutation	Calculate the donor vector $\vec{v}_j^{\kappa+1}$ using the following: $\vec{v}_j^{\kappa+1} = \vec{x}_{r_1}^{\kappa} + F\left(\vec{x}_{r_2}^{\kappa} - \vec{x}_{r_3}^{\kappa}\right)$ The constant F is called the mutation factor and it ranges between [0, 2].
Recombination	Calculate a trial vector $\vec{y}_j^{\kappa+1}$ using the following: $y_{m,j}^{\kappa+1} = \begin{cases} y_{m,j}^{\kappa+1}\ if\ r \le CR\ or\ m = m_{rand} \\ x_{m,j}^{\kappa}\ if\ r > CR\ or\ m \ne m_{rand} \end{cases}$ where, $m \in \{1, 2, \ldots, M\}$ $r \in U[0,1]$ m_{rand} is a random integer from 1 to M.
Selection	Set the value of $\vec{x}_j^{\kappa+1}$ to be: $\vec{x}_j^{\kappa+1} = \begin{cases} \vec{y}_j^{\kappa+1}\ if\ \Phi\left(\vec{y}_j^{\kappa+1}\right) \le \Phi\left(\vec{x}_j^{\kappa}\right) \\ \vec{x}_j^{\kappa}\ otherwise \end{cases}$ $j \in \{1, 2, \ldots, N_p\}$
Repeat in this order until the criteria is reached.	

Figure 1: Differential evolution (DE) procedures

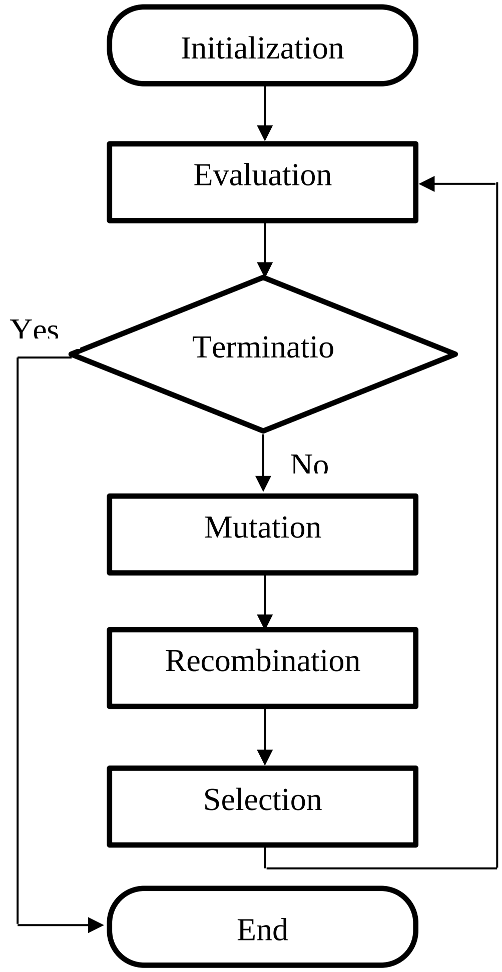

Figure 2: Flow chart of the differential evolution (DE) workflow

At the last generation, the best candidate solution will be the agent that has the lowest cost function. The performance of the algorithm is affected by the values of mutation factor (F), crossover probability (CR), and number of agents (N_p). Therefore, good selection of these parameters is needed to get good results.

3.3.2 Inequality Constraints as the Penalty Approach

The optimization approach used in this work is constrained to obtain the desired solution which satisfies both economic and environment requirements. A constrained optimization problem is a problem in which a cost function is to be minimized (or maximized) subject to some constraints. In such optimization problems, the aim is to find the minimum or maximum cost function and satisfy all predefined constraints. In general, the constrained optimization problem can be written as:

$$\min_{\vec{\alpha}} \Phi(\vec{\alpha}) \tag{4}$$

$$\vec{f}(\vec{\alpha}) = 0, \tag{5}$$

$$\vec{g}(\vec{\alpha}) \leq 0, \tag{6}$$

where,

$\vec{\alpha}$ = Vector of design variables.

Φ = Objective function.

$\vec{f}$ = Vector-valued function that describes the equality constraints.

$\vec{g}$ = Vector-valued function that describes the inequality constraints.

The constrained optimization problem is handled through several methods. One method is to convert the constrained problem to unconstrained problem by adding the constraints in the objective function. Penalty parameters were used in this work by adding them to the objective function. The penalty parameter is a positive number that may increase with each iteration. In each iteration, if all constraints are satisfied, the penalty parameter remains zero. However, the penalty parameter increases with each violation of the constraints. Therefore, the cost function of the unconstrained optimization problem is defined as:

$$\hat{\Phi}_k\left(\vec{\alpha}, \dot{\zeta}\right) = \Phi_k\left(\vec{\alpha}_k\right) + \sum_{j=1}^{N_c} \dot{\zeta}_{k,j}\left[g_{k,j}\left(\vec{\alpha}\right)\right]^a, \tag{7}$$

where,

$$\dot{\zeta}_{k,j} = \begin{cases} 0 & \text{if } g \le 0 \\ \zeta_k \gg 0 & \text{if } g > 0 \end{cases} \tag{8}$$

and ζ_k is a monotonically increasing scalar quantity. The value of a is usually taken as 1 or 2. The cost function presented in this work can be considered as a multiobjective function composed of Φ and $\sum_{j=1}^{N_c} g_j$ with ζ as the weighting parameter that determines the relative importance of the two objectives.

CHAPTER 4: PROBLEM STATEMENT

4.1 Problem Statement

Well locations determine the resultant NPV and pressure distribution. In this work, producers and injectors are placed optimally within the reservoir in such a way maximum NPV is obtained allowing an acceptable pressure variation in the reservoir. This is done through enhancing the well placement optimization approach using a constrained optimization technique. As mentioned earlier, several efforts have been exerted in optimizing well placement through maintaining single or multiple objectives. NPV and VRR were both considered for maximizing profit return and minimizing the environmental effects during field depletion.[1] NPV is a clear and straightforward measure for evaluating investments and projects to decide if it is worth pursuing. All kinds of businesses and companies use NPV as a tool for making decisions about their proposals and plans. However, it is not easy to evaluate formation changes and environmental effects that take place throughout reservoir depletion. The criteria for examining the reservoir health are somehow indefinite and many reservoir properties can contribute in this kind of measurement. VRR generally evaluates the balance between injection and production and hence, it measures the pressure distribution within the reservoir. Reservoir pressure distribution is the main contributor for maintaining reservoir health. So, VRR can be used to indirectly measure the environmental effects during reservoir depletion. VRR affects the reservoir pressure distribution since it compares the volume of fluid injected and the fluid produced. As mentioned earlier, reservoir depletion might cause formation subsidence. Numerous formation subsidence incidents due to reservoir depletion have been reported about subsidence events in Goose Creek, Lost Hills, and Belridge oil fields.

Another concern on well placement optimization is that evaluating certain measurement of the whole reservoir might not give good estimation of the desired objective. For example, using VRR to measure the environmental effects might mislead the development to undesirable consequences since significant positive volume changes in a region of the reservoir might be opposed by significant negative volume changes in another region. This results in major alteration of the voidage replacement distribution that is not measured properly by field VRR. In such cases, field VRR is not efficient for detecting these disparate regional changes. **Figure 3** shows the reservoir average pressure ($\bar{P}$) and regional average pressure ($\overline{P_r}$) of four regions during twenty years of production. The figure shows the difference between $\overline{P_r}$ when considering VRR in optimization.[1] Each $\overline{P_r}$ has its own curve and the maximum difference between them ($\Delta\overline{P_r}$) in this case is 556 psig. Using only $\bar{P}$ in the optimization may result in such high $\Delta\overline{P_r}$. Therefore, VRR or $\bar{P}$ are not enough for balancing the reservoir pressure distribution for the purpose of maintaining the reservoir health and the environmental aspects.

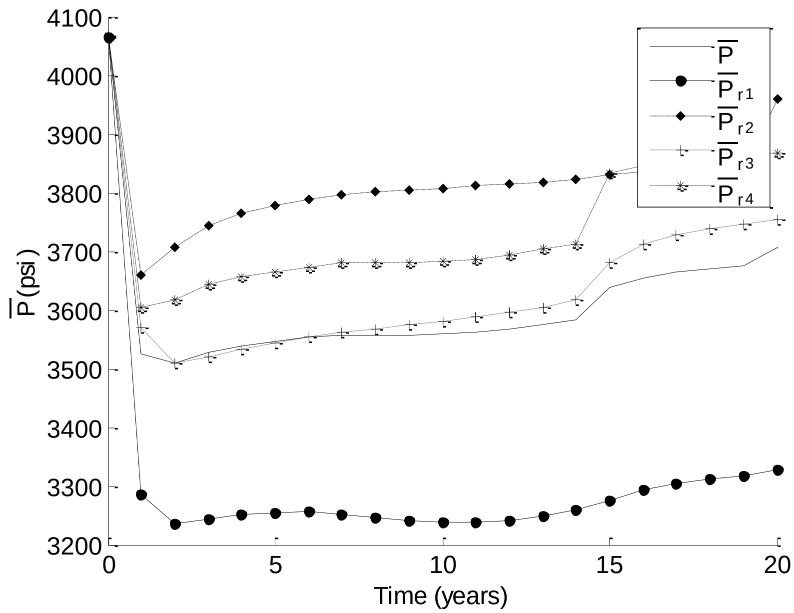

Figure 3: NPV and VRR Optimization shows large $\Delta\overline{P_r}$

CHAPTER 5: OBJECTIVES AND APPROACH

5.1 Objectives and Approach

This work assesses the optimization of NPV subject to regional pressure constraint and average reservoir pressure constraint. To handle the disparate reservoir pressure distribution of the reservoir, regional reservoir pressure ($\overline{P_r}$) is used during the optimization instead of reservoir average pressure ($\bar{P}$). The reservoir is divided into four regions where each region has its own $\overline{P_r}$ and they all should not deviate from certain threshold in order to balance the pressure in the overall reservoir. The principal objectives of this work are:

1. Use the reservoir average pressure instead of VRR as environmental constraint in the optimization.
2. Use regional reservoir average pressure, $\overline{P_r}$.
    a. Divide the reservoir into four regions. The reservoir can be subdivided into several regions in ECLIPSE simulator by using $FIPNUM$ keyword. $FIPNUM$ stands for fluid-in-place regions, as per ECLIPSE definition. Each region has its own average pressure where it is referred to as regional average pressure $\overline{P_r}$.
    b. Optimize well placement in all regions.
    c. Maximize NPV and maintain reservoir pressure variance within a predefined limit.
3. Evaluate two reservoir models:
    a. Channel reservoir with four facies ($75 \times 75 \times 2$)
    b. Heterogeneous reservoir ($64 \times 64 \times 3$)
4. Construct and study different scenarios through developing and coding an objective function for each.
5. Covert the constrained problem to unconstrained one.
6. Use Differential Evolution method, *DE*, for the unconstrained problem.
7. Validate the proposed approach through comparing simulation results.

CHAPTER 6: CASES AND RESULTS

6.1 Reservoir Models

Several scenarios are evaluated to examine the multi-objective well placement approach with NPV and regional reservoir average pressure balance. Four regions within the reservoir are defined for conducting the study and simulating the scenarios. **Table 1** shows the basic parameters used in this work.

Table 1: Reservoir models and their parameters

Attribute	Model 1	Model 2
Reservoir type	Channel with four facies	Heterogeneous
Fluid phases	Oil and water	Oil and water
Reservoir dimensions (grid cells)	$75 \times 75 \times 2$	$64 \times 64 \times 3$
Number of cells	11250	12288
Number of layers	2	3
Number of regions	4	4
Existing wells	0	0
Number of production wells	18	18
Number of Injection wells	12	12
Number of simulation years	30	30

6.2 Study and Scenarios

The two reservoir models were used to assess the effect of using regional reservoir pressure as a constraint instead of using voidage replacement ratio for maintaining environmental restrictions during well placement process. The study evaluated two models; Model 1 ($75 \times 75 \times 2$) and Model 2 ($64 \times 64 \times 3$) and compared the resultant well locations set and reservoir dynamic properties for the reservoir model with different configurations. The aim here is to address the advantage of using regional average pressure ($\overline{P_r}$), to maintain high NPV and balanced reservoir pressure distribution. Following is the list of different cases studied. Note that these cases were conducted in both Model 1 and Model 2.

1. Run and evaluate three cases without optimization. Wells were pre-located in the reservoir using different patterns. These cases were considered as base cases to compare with NPV and regional pressure balance optimization cases.
2. Optimize NPV only and study the effect on regional average pressure. The objective function was built based on NPV only.
3. Optimize both NPV and regional average pressure balance. Difference between regional average pressure ($\Delta\overline{P_r}$) was not allowed to exceed certain value. The objective function was built based on both NPV and regional average pressure.
4. In addition to optimizing both NPV and regional average pressure balance, reservoir average pressure was maintained. Reservoir average pressure curve was improved by not allowing it to drop to certain value. The objective function in this case was built based on NPV, regional average pressure, and overall reservoir average pressure.

6.3 Objective Function

The general form of the used constraint objective function (COF) consists of parameters for NPV, regional average pressure, and overall reservoir average pressure:

$$\Phi_{COF,\kappa} = -NPV_{\kappa} + \sum_{j=1}^{N_c} \dot{\zeta}_{k,j} \left[u_{k,j}\left(\vec{\alpha}\right) \right]^{a} + \sum_{j=1}^{N_c} \dot{\zeta}_{k,j} \left[v_{k,j}\left(\vec{\alpha}\right) \right]^{a} \tag{9}$$

where,

$\Phi_{COF,\kappa}$ = The constrained objective function.

NPV = Net Present Value.

u = The vector-valued function that describes regional average pressure constraint.

v = The vector-valued function that describes reservoir average pressure constraint.

The cost function is minimized using the differential evolution optimization. Each parameter in the above objective function is minimized. So, a negative sign is placed with NPV since our aim is to maximize NPV, not to minimize it. ΔP_r is calculated for balancing regional average pressure. The differential evolution optimization targets minimizing this value to zero which is undesired. Therefore, a threshold is included later to define the maximum allowed difference between regional pressure values. Reservoir average pressure is maintained using ΔP. Similar to ΔP_r, ΔP includes a threshold to account for the maximum allowed pressure drop.

6.4 Model 1 ($75 \times 75 \times 2$)

A reservoir model of 11,250 cells was used in the following scenarios for optimizing NPV and regional pressure balance. The dimension of the reservoir is $75 \times 75 \times 2$. The model is two-phase oil and water system. Four regions were defined in each scenario to evaluate regional pressure difference between all the cases. The reservoir was divided into four equal regions. The number of wells in this model was set to 30 where 18 of them are producers and the other 12 are injectors. The number of simulation years was set to 30. Grid cell dimensions are 200 ft, 200 ft, and 100 ft. The reservoir is channeled with four facies. Production rate was set to 1500 b/d on all producers and the minimum bottomhole pressure in producers was set to 2000 psig. Injection rate was set to 2500 b/d on all injectors and the maximum bottomhole pressure in injectors was set to 6500 psig. **Figure 4** presents permeability distribution (in mD) of this channeled reservoir with four facies. Note the four regions in the model. **Figure 5** presents the porosity distribution of this model.

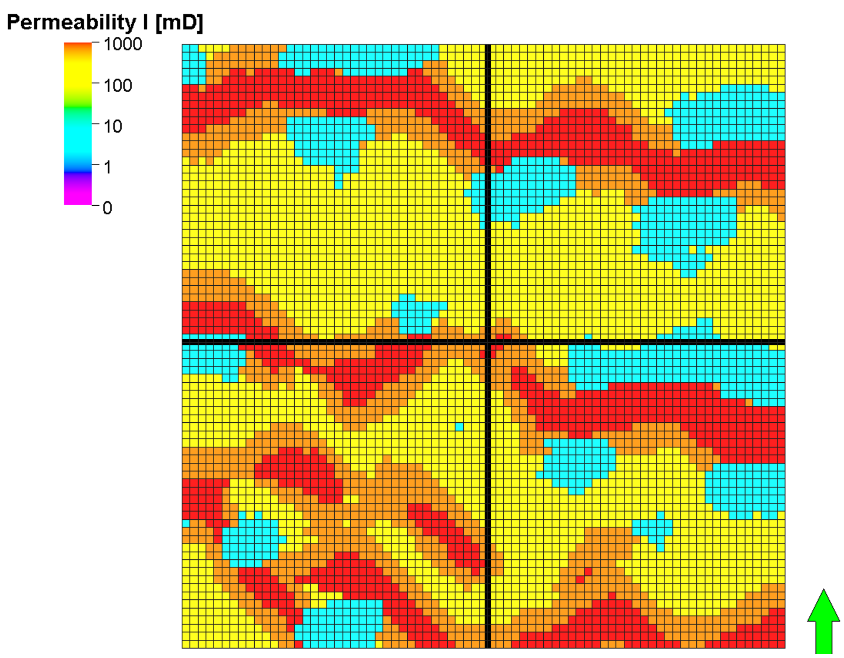

Figure 4: Permeability distribution of Model 1 (Channel with four facies)

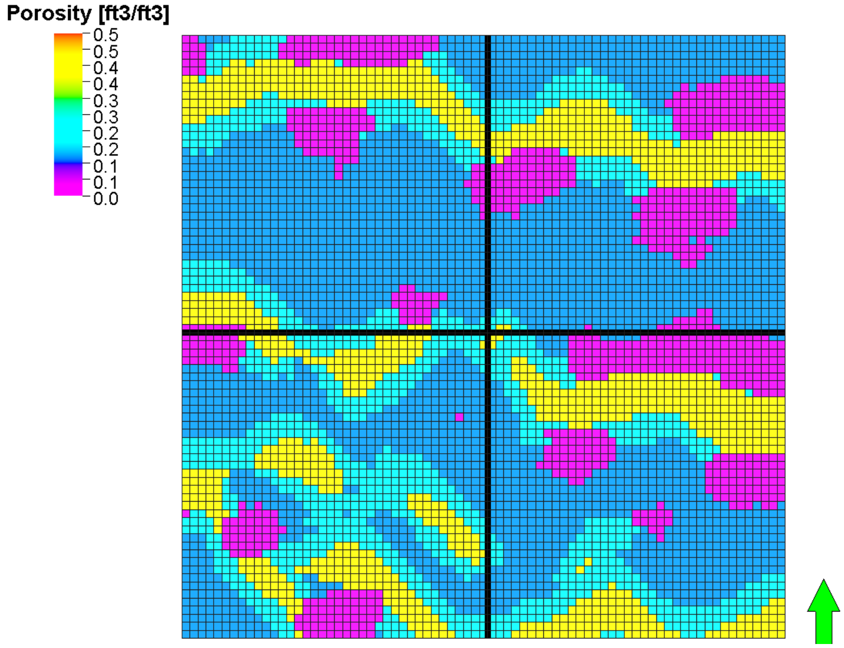

Figure 5: Porosity distribution of Model 1 (Channel with four facies)

6.4.1 Well Location Patterns

Sometimes the development follows certain type of well patterns configuration which depends on reservoir geometries and locations. For a reservoir with simple properties, such as a high permeability reservoir, only few wells might be needed since a single well may produce oil from a very large volume around the wellbore. As the complexity of the reservoir geometry increases, well location determination becomes more significant especially for heterogeneous reservoirs. For that reason, an optimization was carried out in order to find the optimum well locations that satisfy certain objectives. In this work, three different well distribution patterns are evaluated to compare their results with the optimization cases. So, the results of these well patterns were considered as the base for evaluating the proposed constrined optimization and for coming up with decisions when looking at results. Note that no optimization was carried out here in these patterns.

Pattern 1

The first pattern presented in **Figure 6** distributes wells by alternating producers and injectors columns. Some producers and injectors are placed very close to the borders of the regions which might result in major contribution of these wells to more than one region.

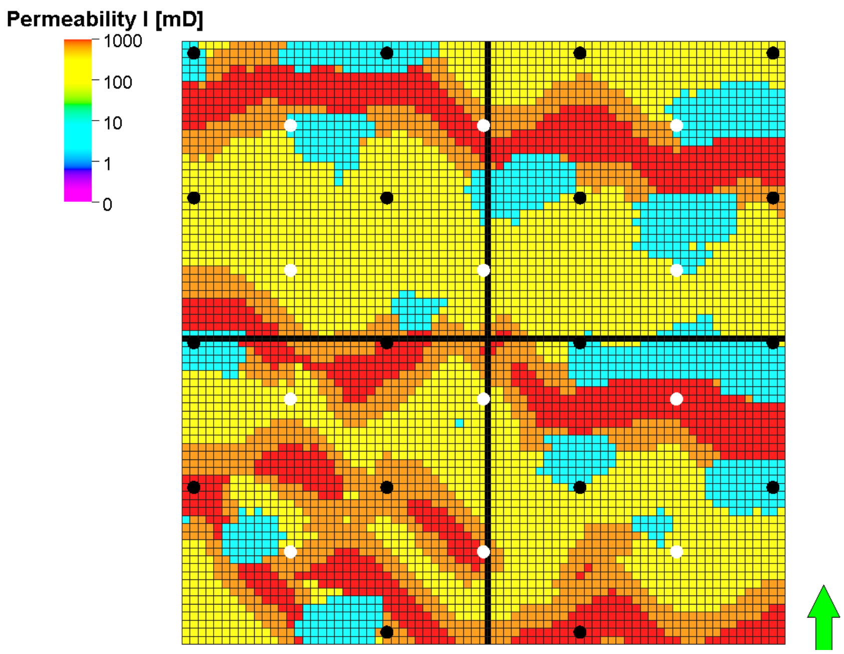

Figure 6: Well distribution of Pattern 1 (Model 1). Black circles represent producers and white circles represent injectors.

Having this well distribution pattern, the model resulted in an NPV of 7.11×10^{9} after 30 years. Reservoir average pressure drops by 1151 psig as maximum during the 30 years (See **Figure 7**). **Figure 8** presents the liquid production cumulative curves of this case. **Figure 9** and **Figure 10** present reservoir average pressure after one year of simulation and after 30 years of simulation, respectively. Notice how the pressure drops in all regions. **Figure 11** and **Figure 12** present water saturation maps in different years. Since this is a channel reservoir, wells located in high permeability and high porosity, have more effect in sweeping out the oil.

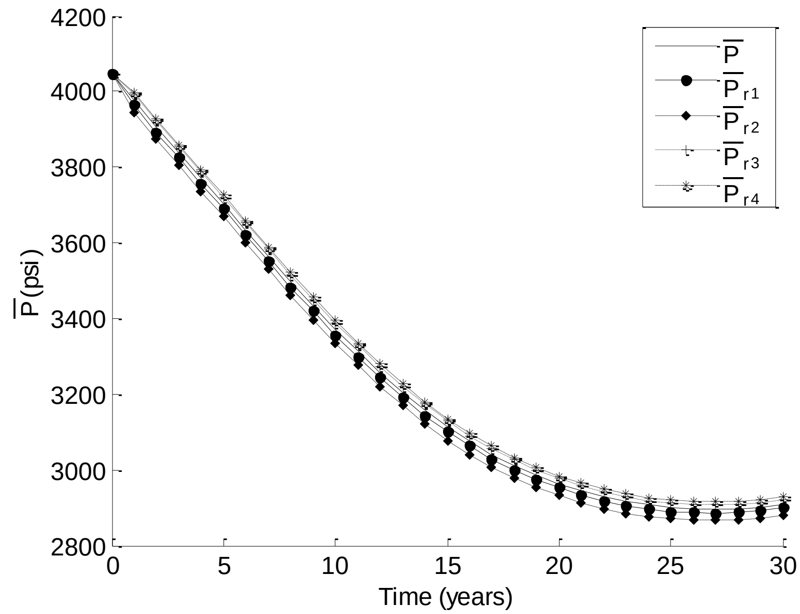

Figure 7: Regional average pressure for Pattern 1 case (Model 1)

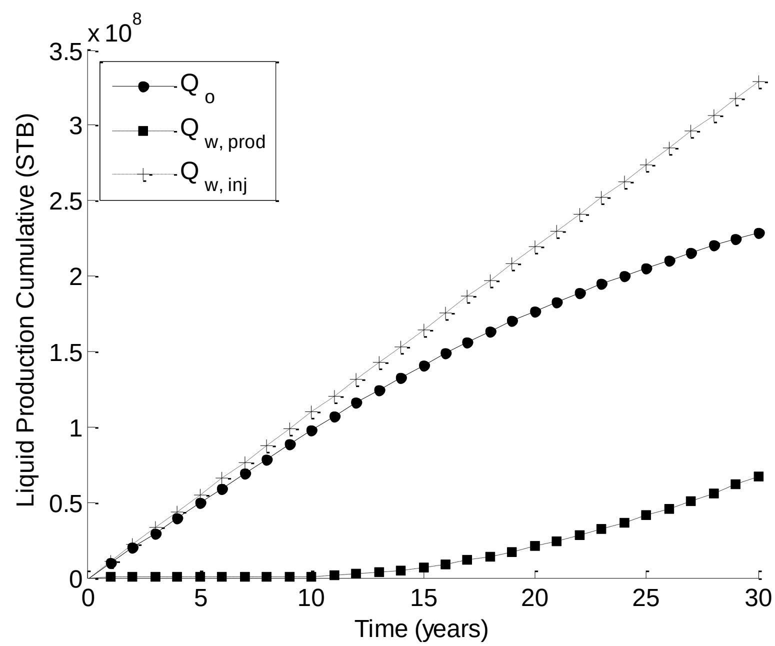

Figure 8: Liquid production cumulative curves for Pattern 1 case (Model 1)

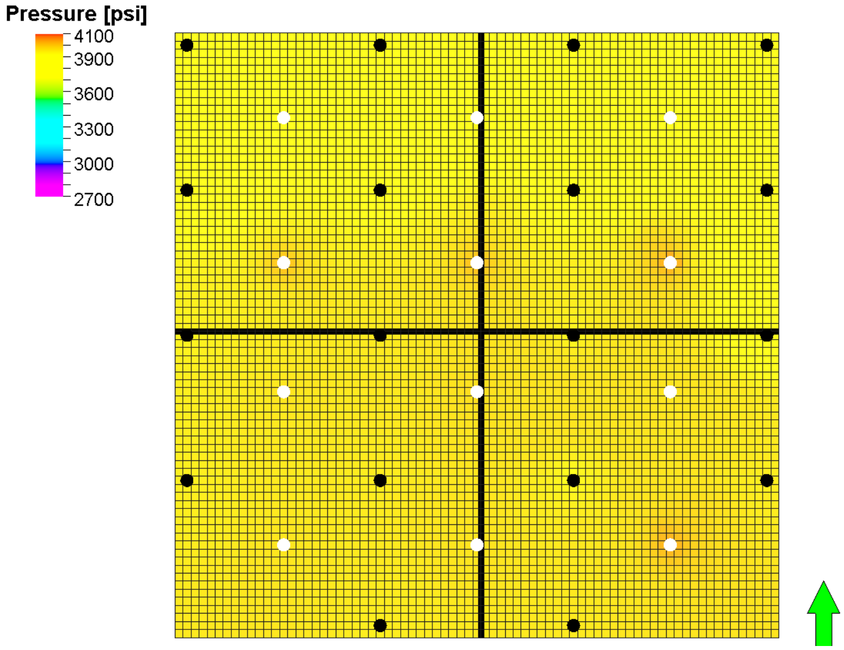

Figure 9: Reservoir average pressure after one year for Pattern 1 (Model 1). Black circles represent producers and white circles represent injectors.

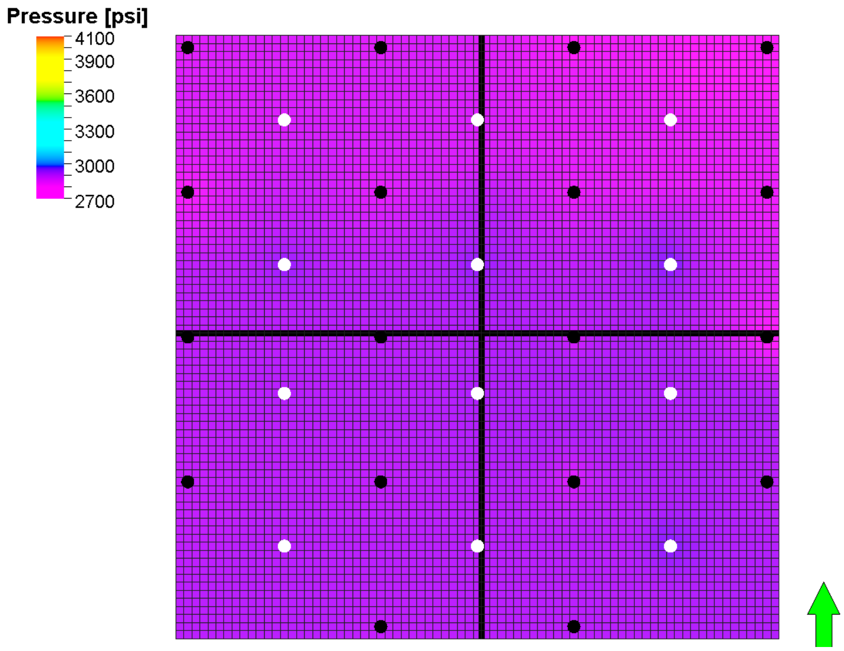

Figure 10: Reservoir average pressure after 30 years for Pattern 1 (Model 1). Black circles represent producers and white circles represent injectors.

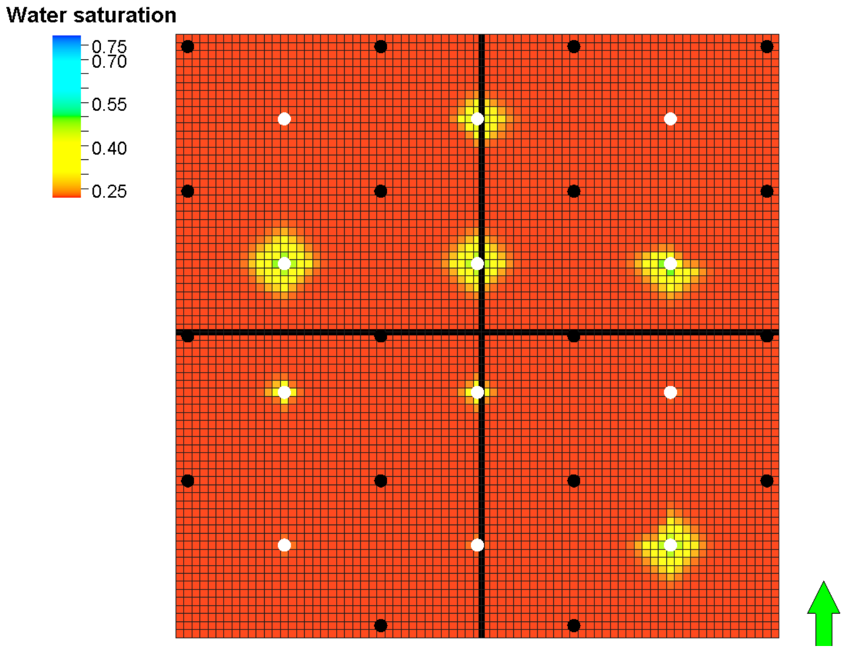

Figure 11: Reservoir water saturation after one year for Pattern 1 (Model 1). Black circles represent producers and white circles represent injectors.

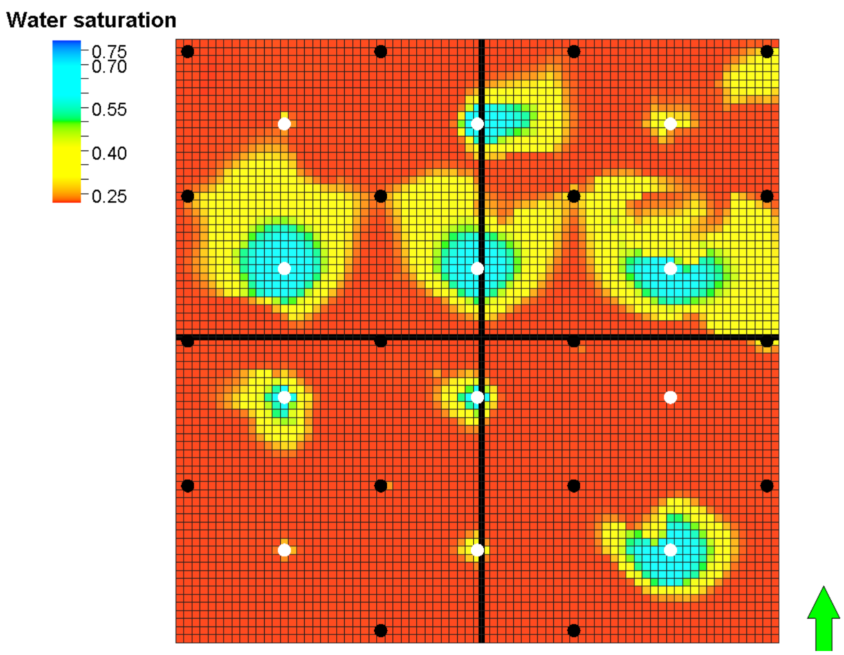

Figure 12: Reservoir water saturation after 30 years for Pattern 1 (Model 1). Black circles represent producers and white circles represent injectors.

Pattern 2

The second pattern presented in **Figure 13** distributes wells by placing the injectors at the edges of the model whereas the producers are placed inside the reservoir. Some producers are placed very close to the borders of the regions which might result in major contribution of these wells in more than one region.

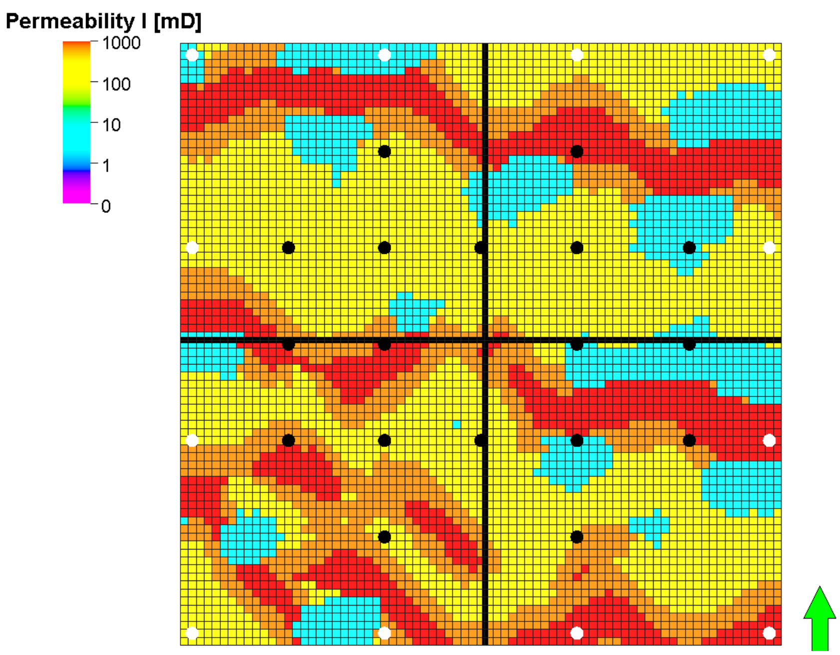

Figure 13: Well distribution of Pattern 2 (Model 1). Black circles represent producers and white circles represent injectors.

Having this well distribution pattern, the model resulted in an NPV of 6.93×10^{9} after 30 years. Reservoir average pressure drops 1180 psig as maximum during 30 years (See **Figure 14**). **Figure 15** presents the liquid production cumulative curves of this case. **Figure 16** and **Figure 17** present reservoir average pressure after one year of simulation and after 30 years of simulation, respectively. Notice how the pressure drops in all regions. **Figure 18** and **Figure 19** present water saturation maps in different years. Since this is a channel reservoir, wells located in high permeability and high porosity, have more effect in sweeping out the oil.

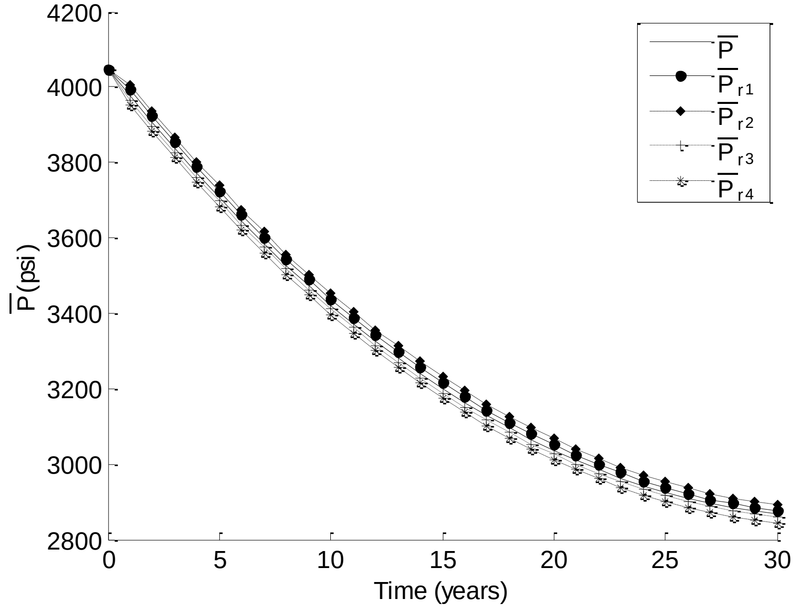

Figure 14: Regional average pressure for Pattern 2 case (Model 1)

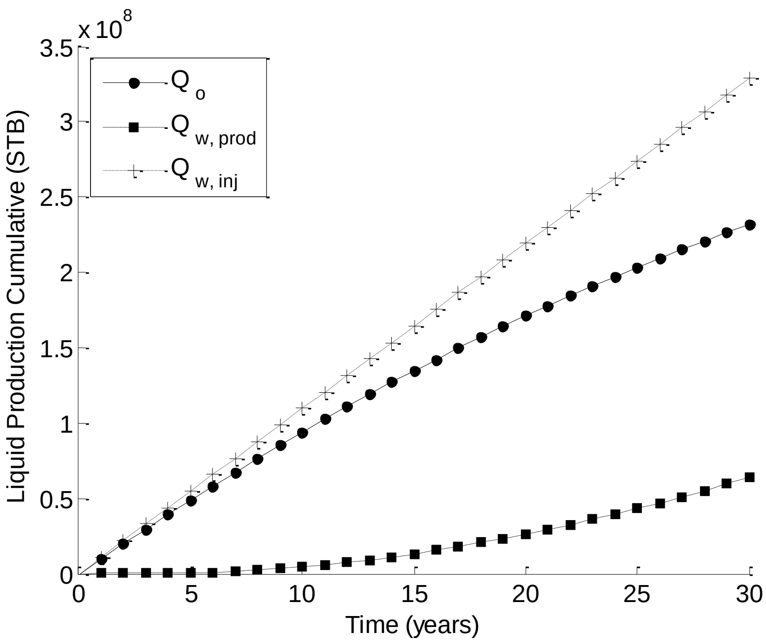

Figure 15: Liquid production cumulative curves for Pattern 2 case (Model 1)

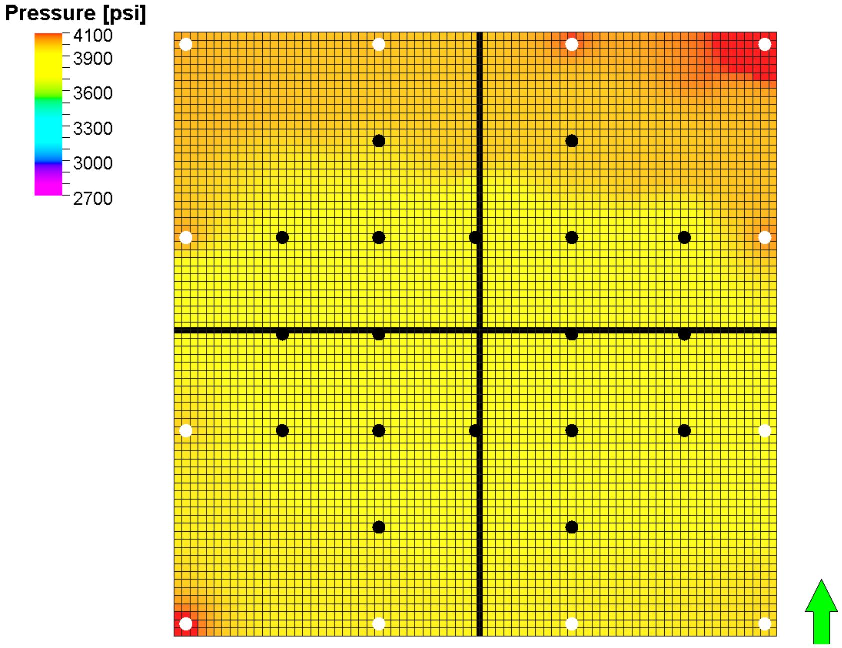

Figure 16: Reservoir average pressure after one year for Pattern 2 (Model 1). Black circles represent producers and white circles represent injectors.

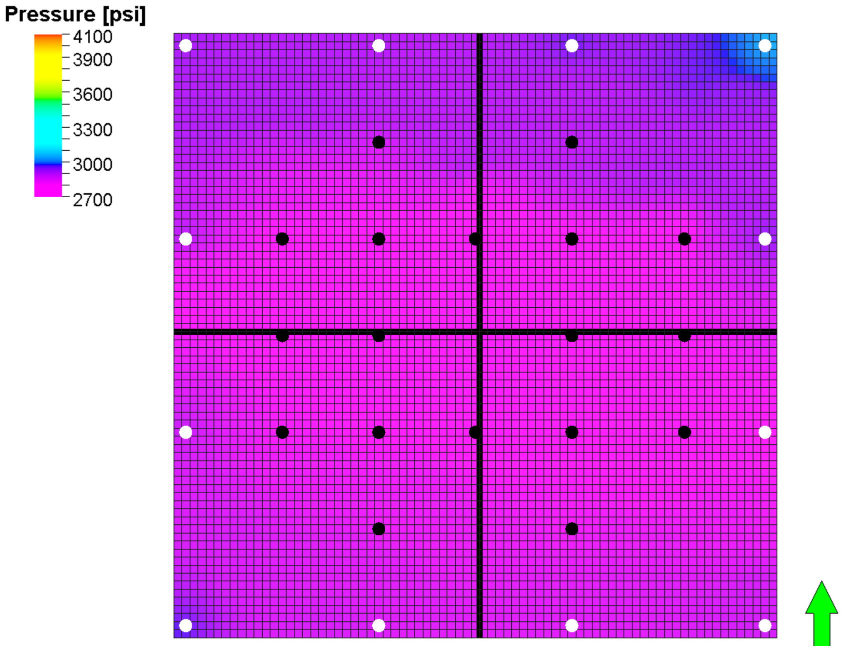

Figure 17: Reservoir average pressure after 30 years for Pattern 2 (Model 1). Black circles represent producers and white circles represent injectors.

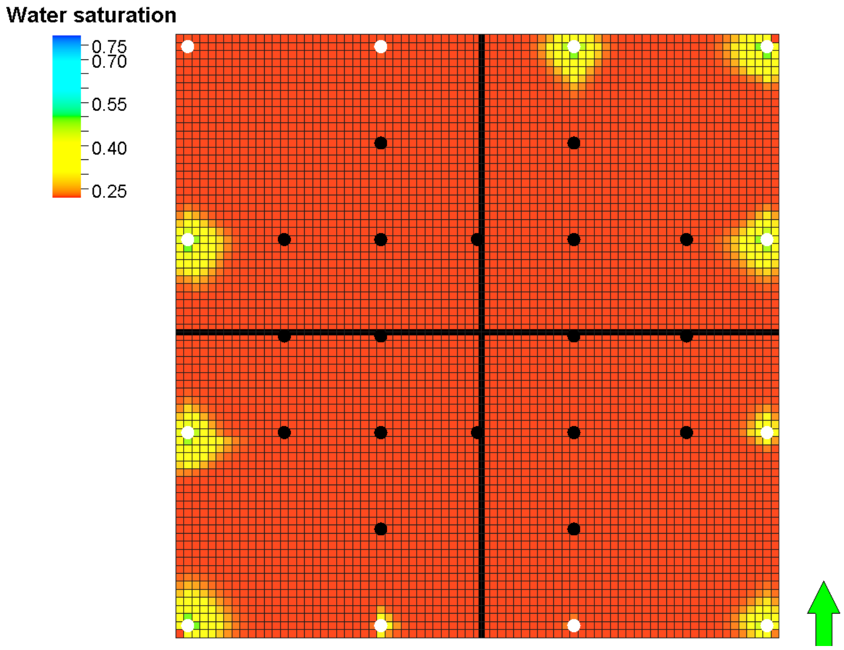

Figure 18: Reservoir water saturation after one year for Pattern 2 (Model 1). Black circles represent producers and white circles represent injectors.

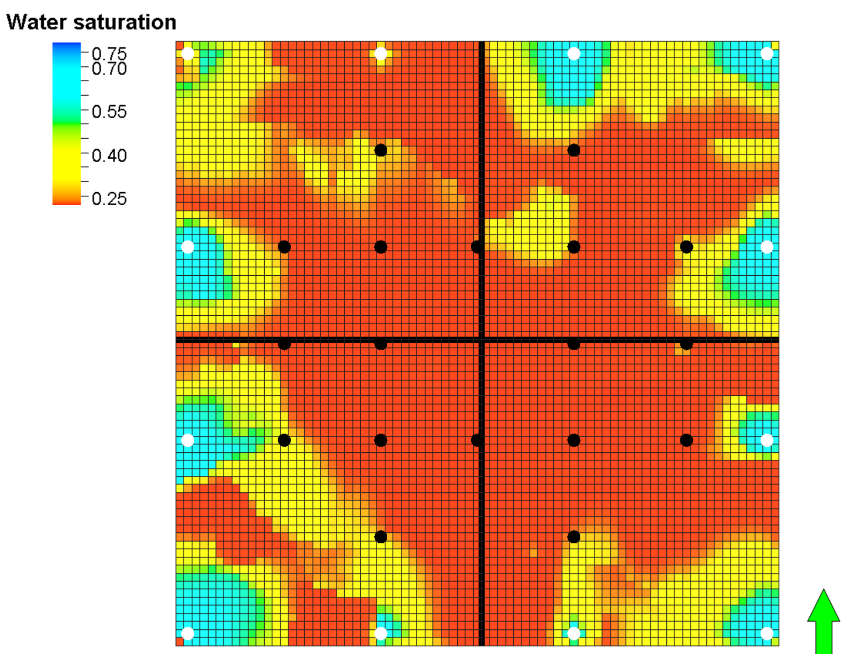

Figure 19: Reservoir water saturation after 30 years for Pattern 2 (Model 1). Black circles represent producers and white circles represent injectors.

Pattern 3

The third pattern presented in **Figure 20** distributes wells by alternating producers and injectors columns. Wells were distributed in a way similar to that in Pattern 1, but with small difference. Some producers and injectors are placed very close to the borders of the regions which might result in major contribution of these wells in more than one region.

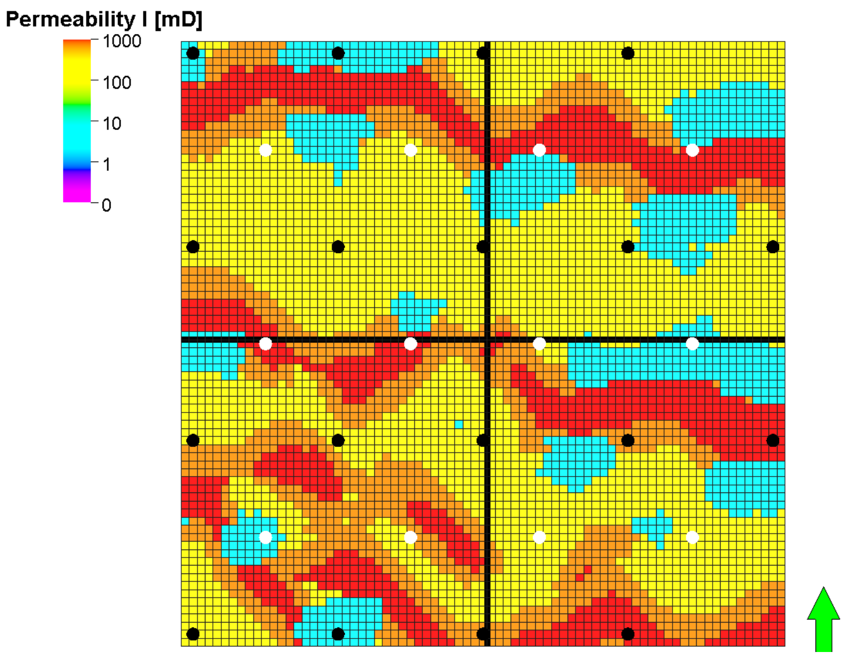

Figure 20: Well distribution of Pattern 3 (Model 1). Black circles represent producers and white circles represent injectors.

The above well distribution pattern resulted in an NPV of 7.04×10^{9} after 30 years. Reservoir average pressure drops by 568 psig as maximum during 30 years (See **Figure 21**). **Figure 22** presents the liquid production cumulative curves of this case. **Figure 23** and **Figure 24** present reservoir average pressure after one year of simulation and after 30 years of simulation, respectively. Notice how the pressure drops in all regions. **Figure 25** and **Figure 26** present water saturation maps in different years. Again, since the model is channeled, wells located in high permeability and high porosity, have more effect in sweeping out the oil.

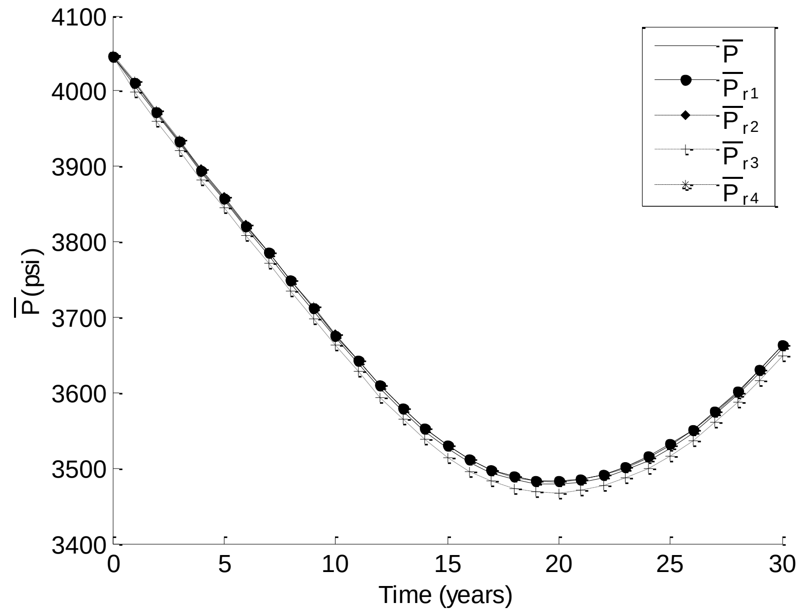

Figure 21: Regional average pressure for Pattern 3 case (Model 1)

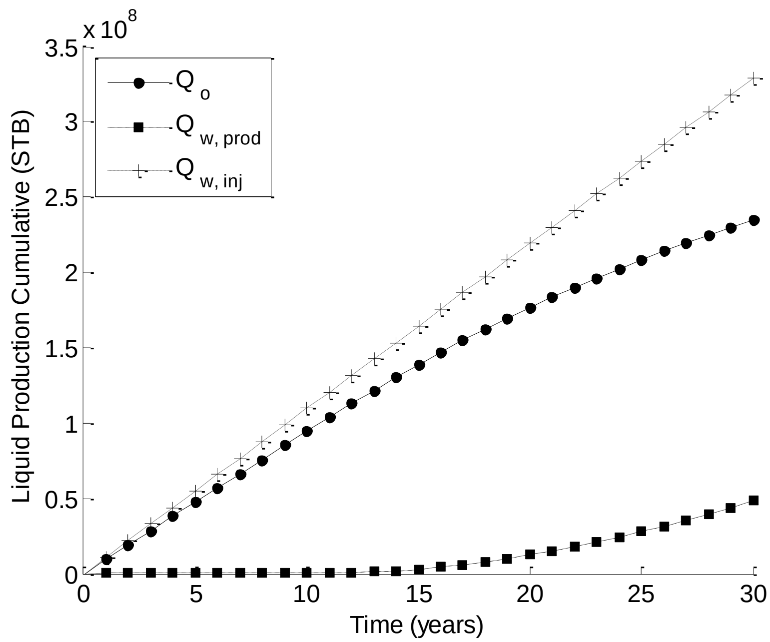

Figure 22: Liquid production cumulative curves for Pattern 3 case (Model 1)

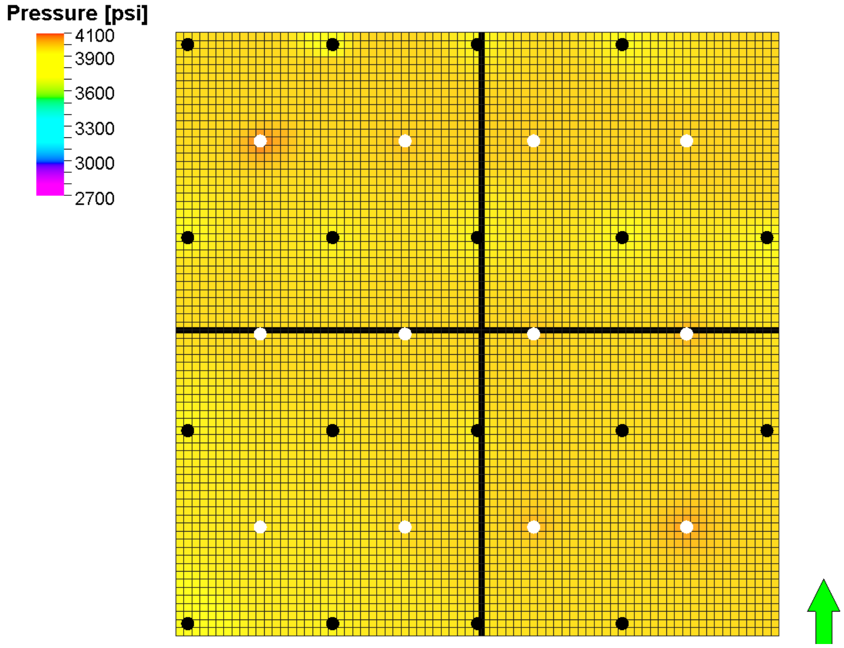

Figure 23: Reservoir average pressure after one year for Pattern 3 (Model 1). Black circles represent producers and white circles represent injectors.

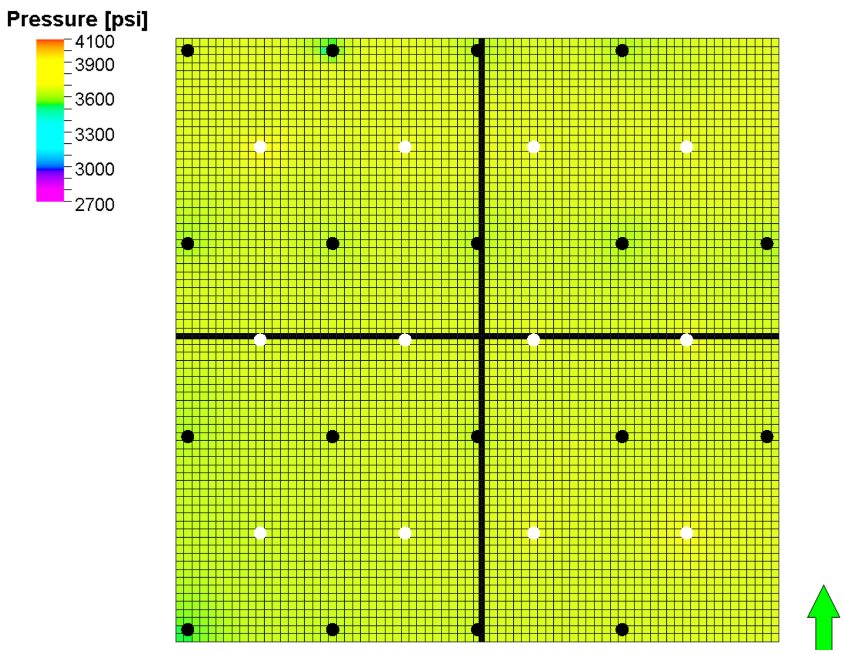

Figure 24: Reservoir average pressure after 30 years for Pattern 3 (Model 1). Black circles represent producers and white circles represent injectors.

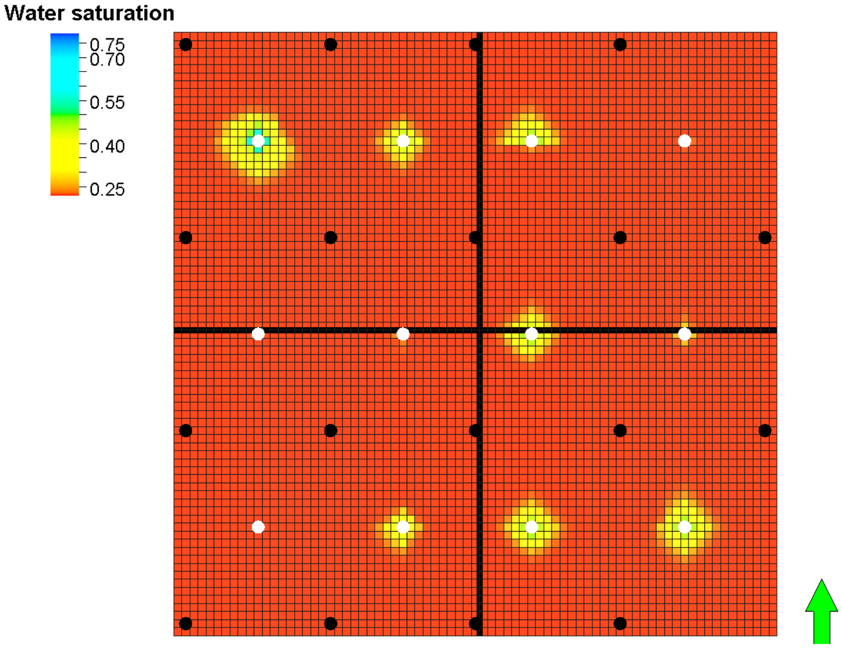

Figure 25: Reservoir water saturation after one year for Pattern 3 (Model 1). Black circles represent producers and white circles represent injectors.

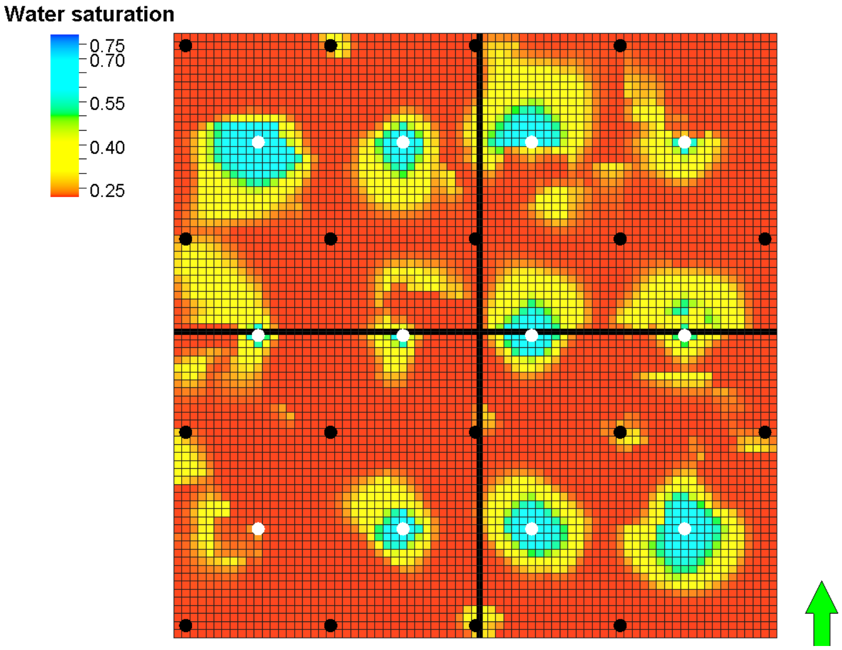

Figure 26: Reservoir water saturation after 30 years for Pattern 3 (Model 1). Black circles represent producers and white circles represent injectors.

6.4.2 Case 1: Optimization of NPV Alone

In NPV optimization, we focus on increasing NPV only without giving attention to regional pressure balance. Basically, the objective function in this case is:

$$\Phi_{NPV,\kappa} = -NPV_{\kappa} \tag{10}$$

The above objective function is called an unconstrained objective function since it takes care of one objective only with no constraints. This optimization resulted in the well distribution shown in **Figure 27**. The resultant well distribution results in an NPV of 7.78×10^{9} after 30 years. As expected, NPV in this case is higher than those for the evaluated well pattern cases. However, reservoir average pressure drops 1761 psig during 30 years (See **Figure 28**) which is higher than ΔP of the well pattern cases (1151 psig, 1180 psig, 568 psig). This pressure drop is expected since the optimization focuses on NPV only without looking at reservoir pressure. Moreover, regional pressure is affected where a difference of 338.93 psig is noted between $\overline{P}_{r2}$ and $\overline{P}_{r3}$. This difference is much higher than the maximum ΔP_r values for pattern cases evaluated (See **Table 2**). Note also that some producers and injectors are clustered in one region and there is no balance in well locations among all regions. **Figure 29** presents the liquid production cumulative curves of this case. **Figure 30** and **Figure 31** present reservoir average pressure after one year of simulation and after 30 years of simulation, respectively. Notice how the pressure drops in all regions differently. Region 1 (Top left corner) and region 2 (Top right corner) have higher pressure which resulted in high ΔP_r between $\overline{P}_{r2}$ and $\overline{P}_{r3}$ as mentioned earlier. **Figure 32** and **Figure 33** present water saturation maps in different years. Unlike what have been seen in the patterns cases, saturation is not uniform where scattered sweeping spots are noticed in the saturation maps.

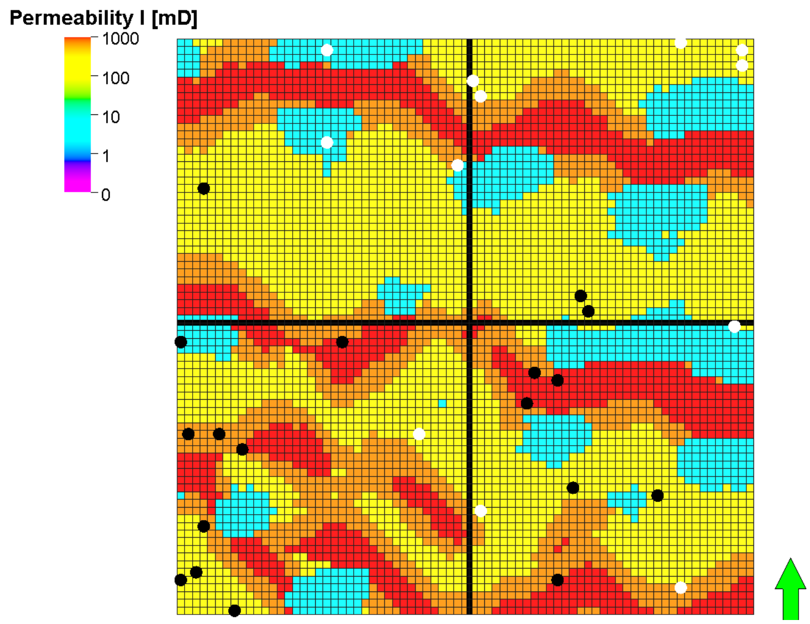

Figure 27: Well distribution of Case 1 (Model 1). Black circles represent producers and white circles represent injectors.

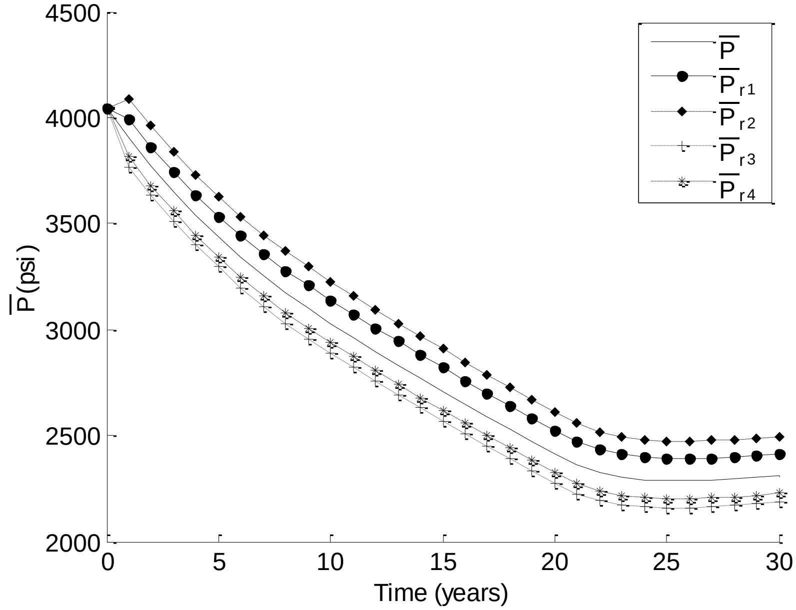

Figure 28: Regional average pressure for Case 1 (Model 1)

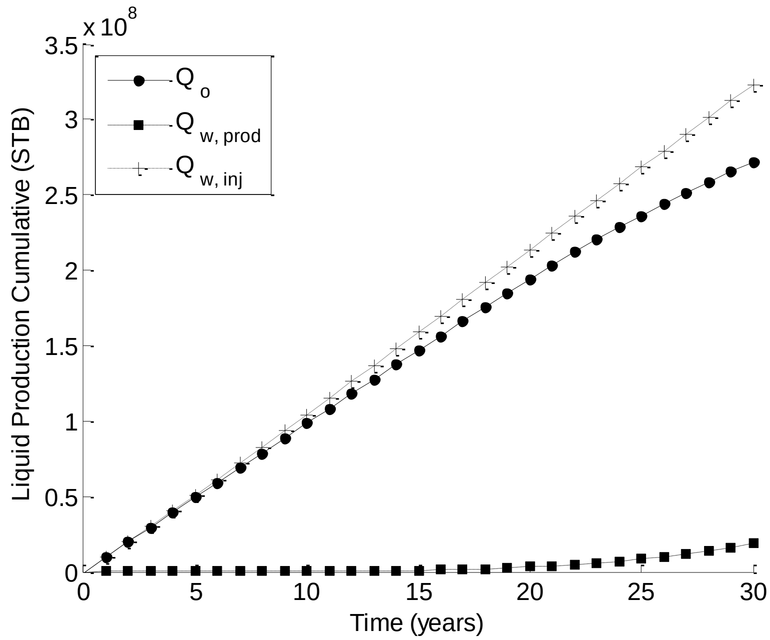

Figure 29: Liquid production cumulative curves for Case 1 (Model 1)

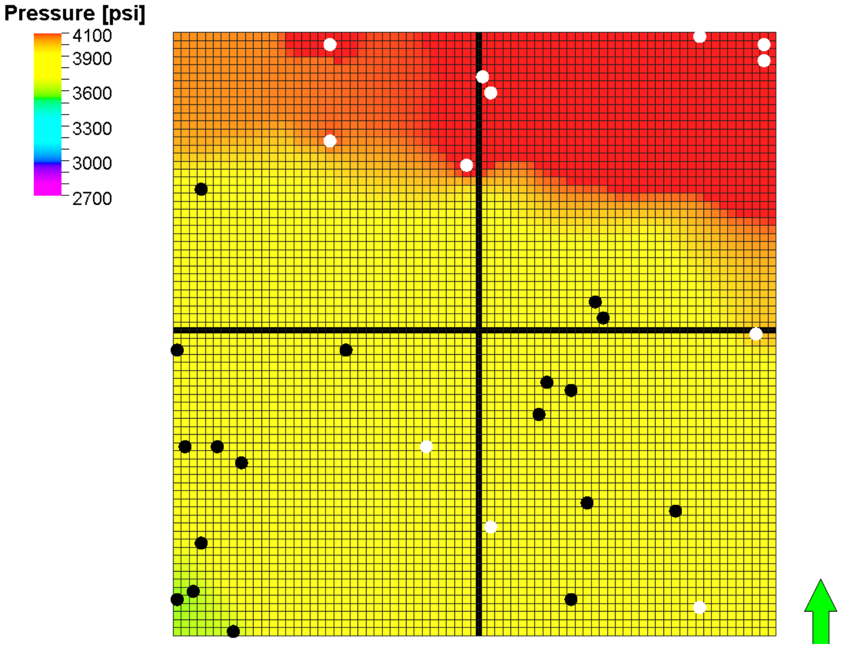

Figure 30: Reservoir average pressure after one year for Case 1 (Model 1). Black circles represent producers and white circles represent injectors.

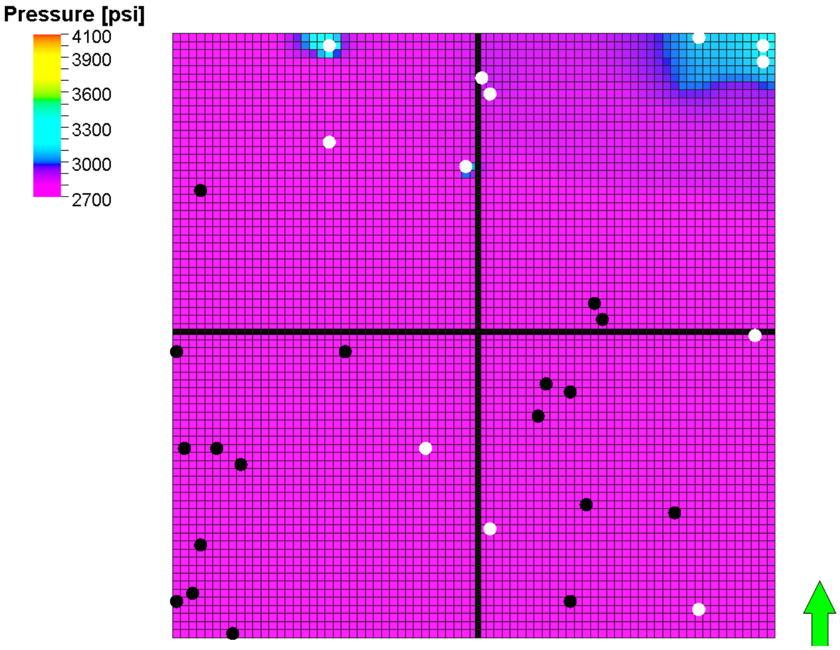

Figure 31: Reservoir average pressure after 30 years for Case 1 (Model 1). Black circles represent producers and white circles represent injectors.

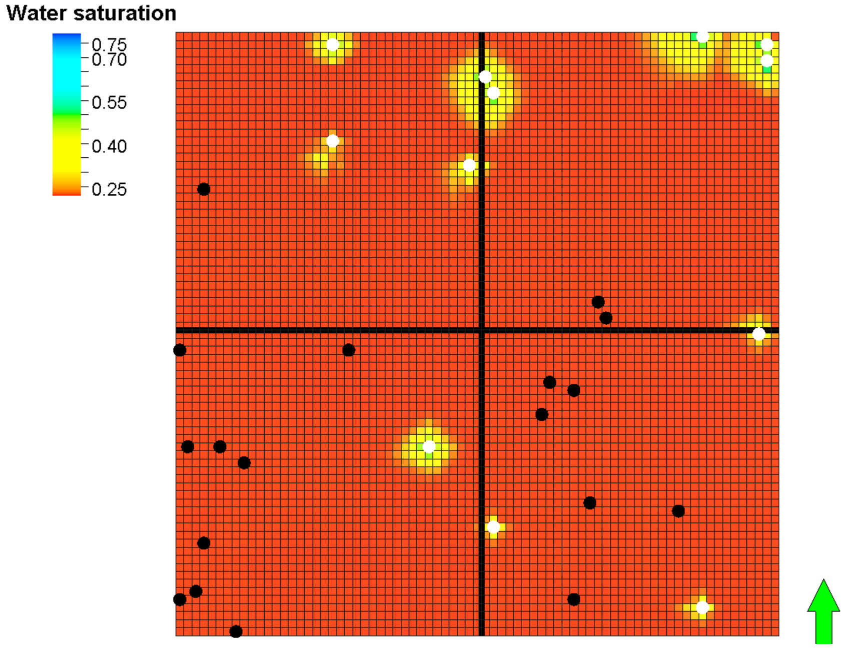

Figure 32: Reservoir water saturation after one year for Case 1 (Model 1). Black circles represent producers and white circles represent injectors.

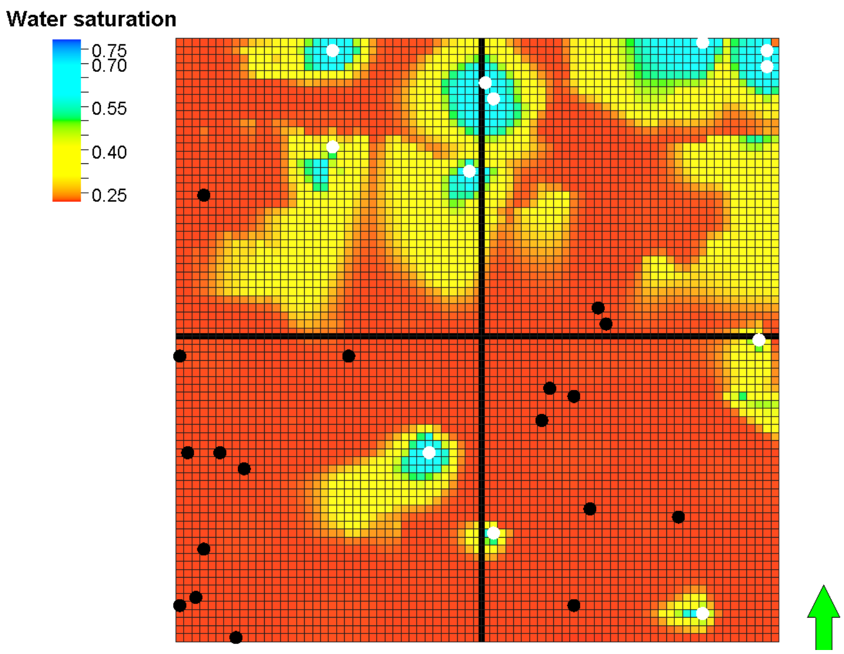

Figure 33: Reservoir water saturation after 30 years for Case 1 (Model 1). Black circles represent producers and white circles represent injectors.

6.4.3 Case 2: Optimization of NPV Subject to Regional Pressure Constraint

In previous cases, well placement was first optimized by maximizing NPV only which resulted in large reservoir average pressure drop and in an increased difference between regional average pressure. In this case, the difference between regional average pressure is included in the optimization function as a constraint in order to minimize that difference. The objective function becomes now a constrained objective function. Below is the objective function used in this case:

$$\Phi_{COF,\kappa} = -NPV_\kappa + \sum_{j=1}^{N_c} \dot{\zeta}_{k,j} \left[u_{k,j}\left(\vec{\alpha}\right) \right]^a \tag{11}$$

This optimization resulted in the well distribution shown in **Figure 34**. The resultant well distribution results in an NPV of 7.53×10^9 after 30 years. NPV in this case is still higher than those for the evaluated well pattern cases. However, NPV in this case is less than that for NPV optimization case. This reduction in NPV is the cost for adding another objective in the objective function. Reservoir average pressure drops by 1819 psig during 30 years (See **Figure 35** and **Table 2**) which is higher than ΔP of the well pattern cases (1151 psig, 1180 psig, 568 psig) and is almost similar to that for NPV optimization case (1761 psig). This pressure drop is expected since the optimization focuses on increasing NPV and minimizing regional pressure only without looking at overall reservoir average pressure. Regional average pressure difference, however, is reduced from 338.93 psig to 81.85 psig. Note also that well distribution is balanced among the four regions. **Figure 36** presents the liquid production cumulative curves of this case. **Figure 37** and **Figure 38** present reservoir average pressure for different years of simulation. Notice how the pressure drops in all regions. Unlike the previous case, all regions have almost the same pressure distribution. **Figure 39** and **Figure 40** present water saturation maps in different years. Saturation is distributed in a way better than the previous case where sweeping spots are noticed in all regions in the saturation maps.

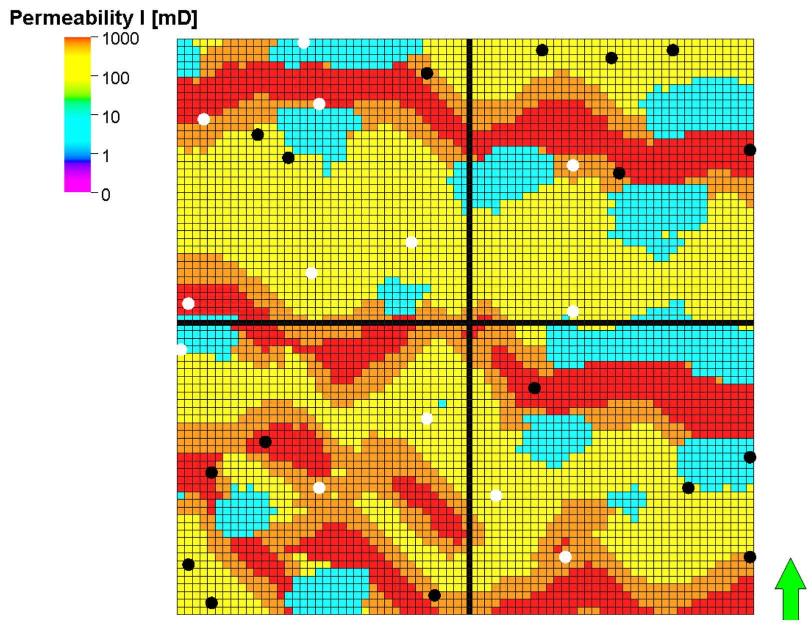

Figure 34: Well distribution of Case 2 (Model 1). Black circles represent producers and white circles represent injectors.

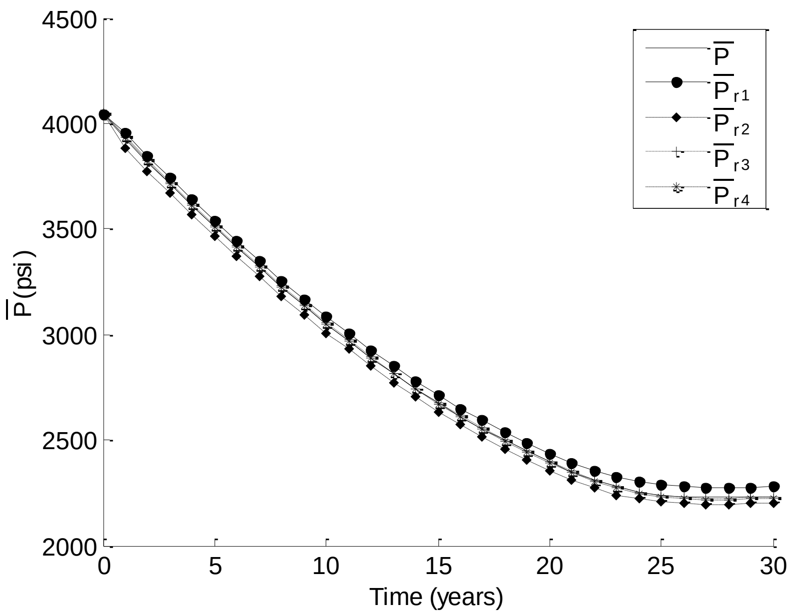

Figure 35: Regional average pressure for Case 2 (Model 1)

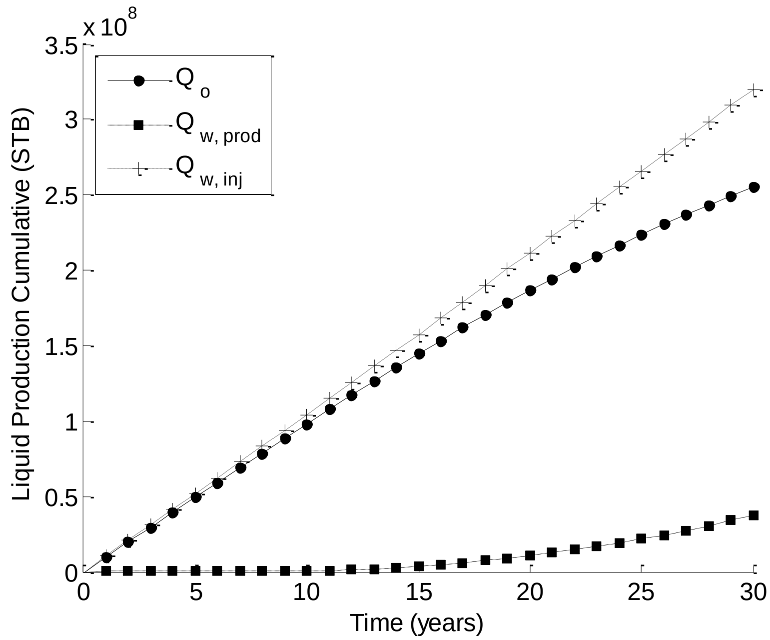

Figure 36: Liquid production cumulative curves for Case 2 (Model 1)

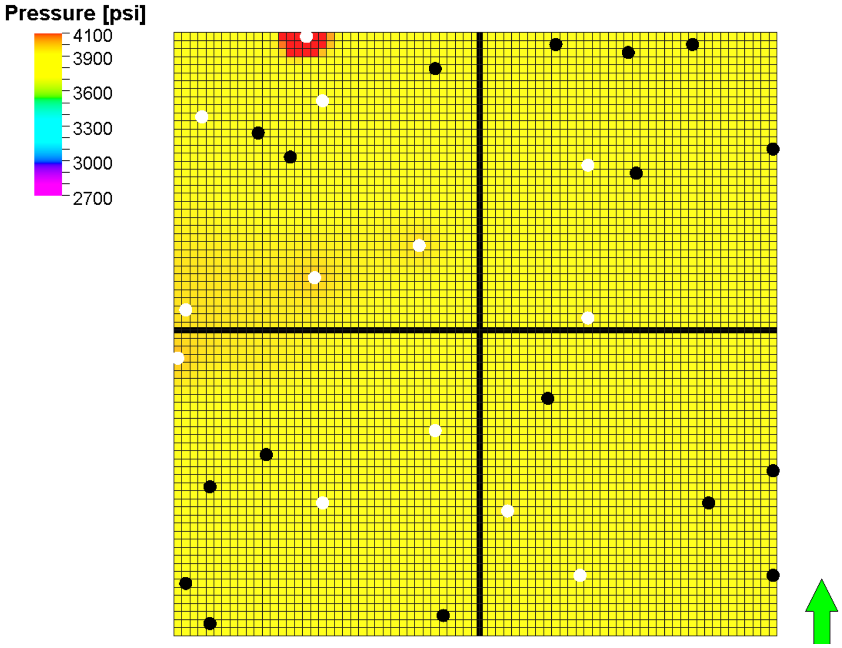

Figure 37: Reservoir average pressure after one year for Case 2 (Model 1). Black circles represent producers and white circles represent injectors.

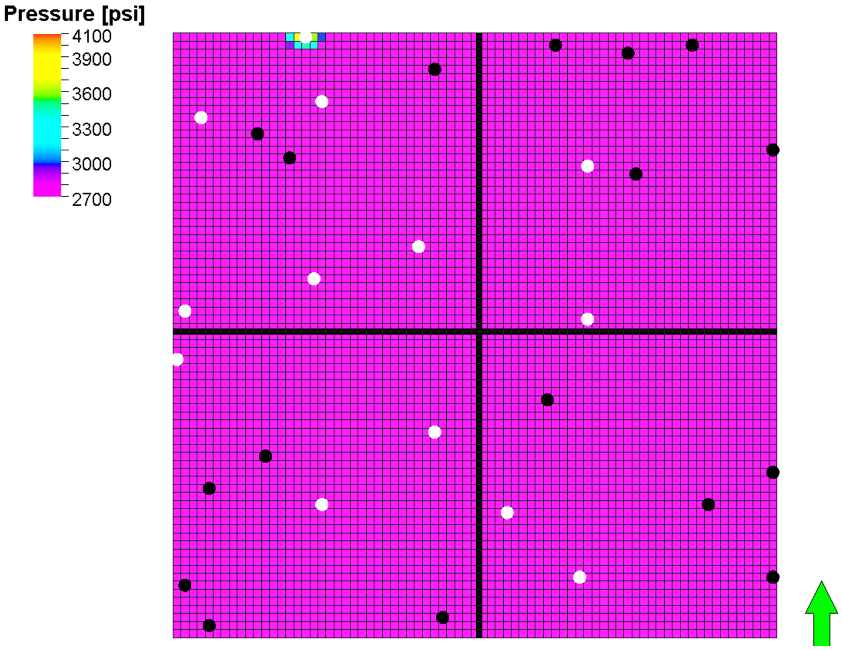

Figure 38: Reservoir average pressure after 30 years for Case 2 (Model 1). Black circles represent producers and white circles represent injectors.

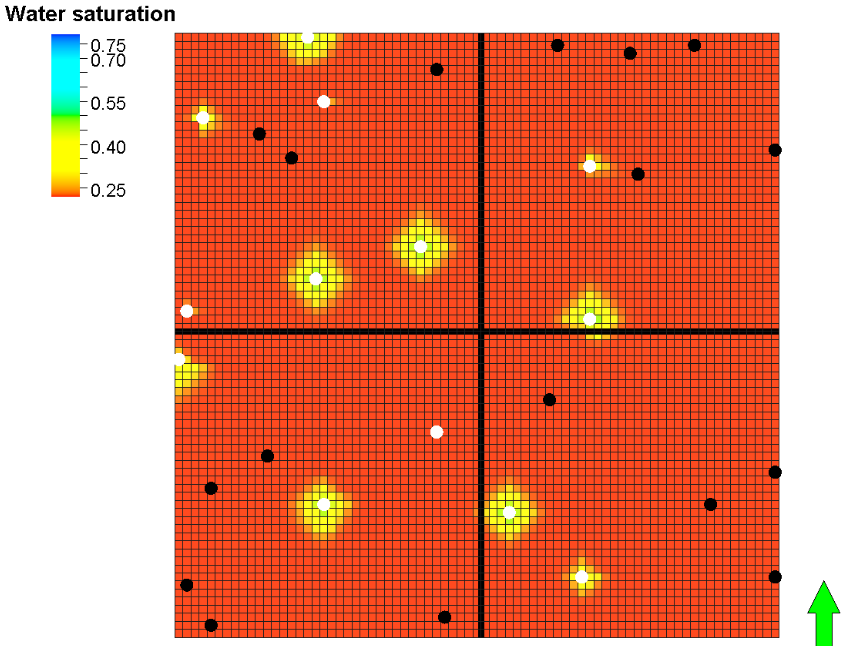

Figure 39: Reservoir water saturation after one year for Case 2 (Model 1). Black circles represent producers and white circles represent injectors.

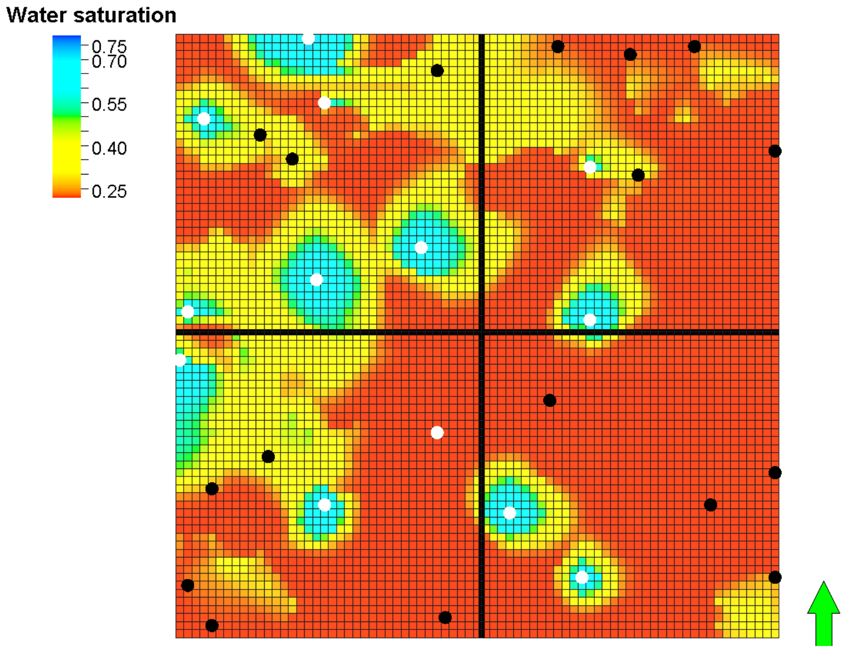

Figure 40: Reservoir water saturation after 30 years for Case 2 (Model 1). Black circles represent producers and white circles represent injectors.

6.4.4 Case 3: Optimization of NPV Subject to Regional Pressure Constraint and Average Reservoir Pressure Constraint

In previous case, well placement is optimized by increasing NPV and minimizing regional pressure difference only. In that case, the difference between regional average pressure is minimized as desired. However, that case resulted in large reservoir average pressure drop which is similar to that case of NPV optimization. In this case, the difference between reservoir average pressure and reservoir initial pressure is included in the optimization function in order to minimize pressure drop. In this case reservoir average pressure is allowed to drop by 500 psig as maximum. Below is the objective function used in this case:

$$\Phi_{COF,\kappa} = -NPV_{\kappa} + \sum_{j=1}^{N_c} \dot{\zeta}_{k,j} \left[u_{k,j}\left(\vec{\alpha}\right) \right]^a + \sum_{j=1}^{N_c} \dot{\zeta}_{k,j} \left[v_{k,j}\left(\vec{\alpha}\right) \right]^a \quad (12)$$

This optimization resulted in the well distribution shown in **Figure 41**. The resultant well distribution results in an NPV of 7.25×10^{9} after 30 years. NPV in this case is still higher than those for the evaluated well pattern cases. However, NPV in this case is less than those for NPV optimization and the multi-objective optimization cases. As seen in the previous case, as we add more constraints to the objective function, NPV gets reduced. Maximum reservoir average pressure drop is 741 psig during 30 years (See **Figure 42** and **Table 2**) which is less than ΔP of those all previous cases. Maximum regional average pressure difference is 91.39 psig which is almost the same as the previous case. **Figure 43** presents the liquid production cumulative curves of this case. **Figure 44** and **Figure 45** present reservoir average pressure for different years of simulation. Notice how the pressure drops in all regions and all regions have almost the same pressure distribution. **Figure 46** and **Figure 47** present water saturation maps in different years. Saturation distribution is improved in this case where sweeping spots are distributed in all regions in the saturation maps.

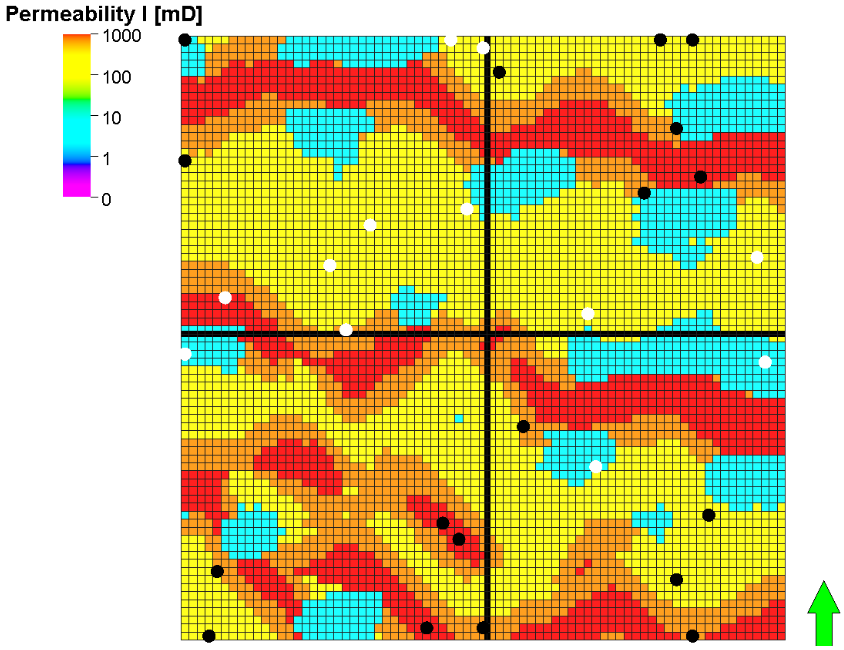

Figure 41: Well distribution of Case 3 (Model 1). Black circles represent producers and white circles represent injectors.

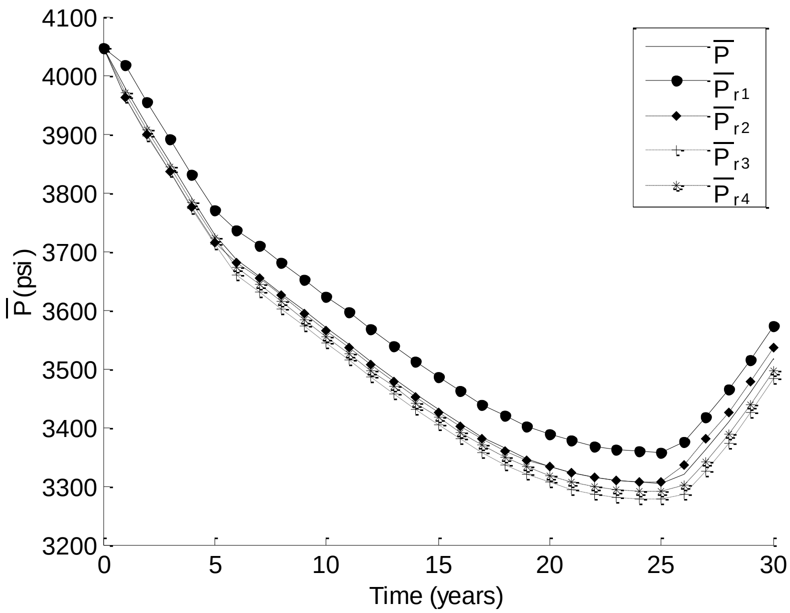

Figure 42: Regional average pressure for Case 3 (Model 1)

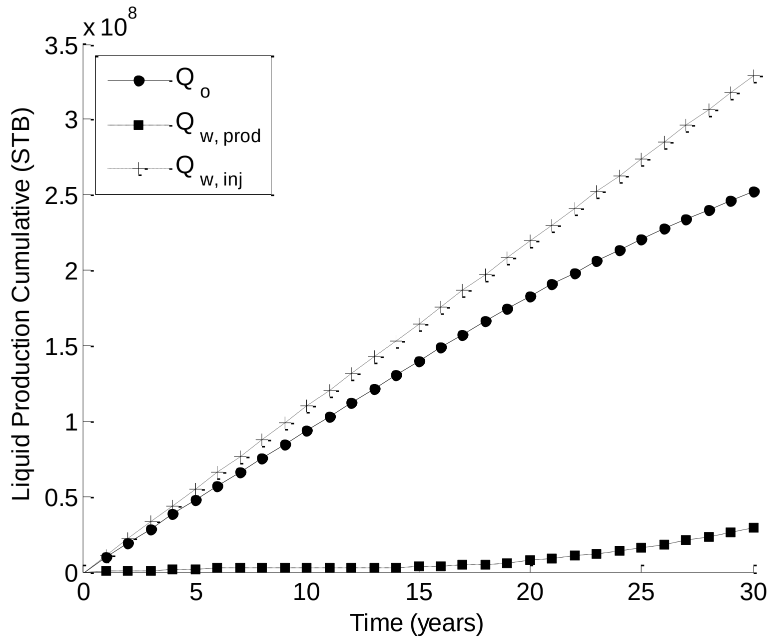

Figure 43: Liquid production cumulative curves for Case 3 (Model 1).

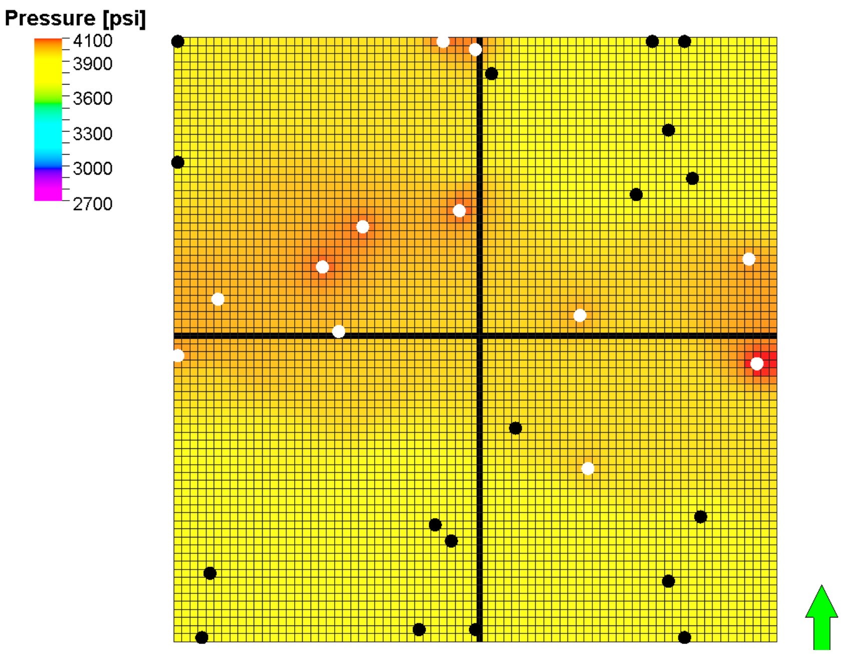

Figure 44: Reservoir average pressure after one year for Case 3 (Model 1). Black circles represent producers and white circles represent injectors.

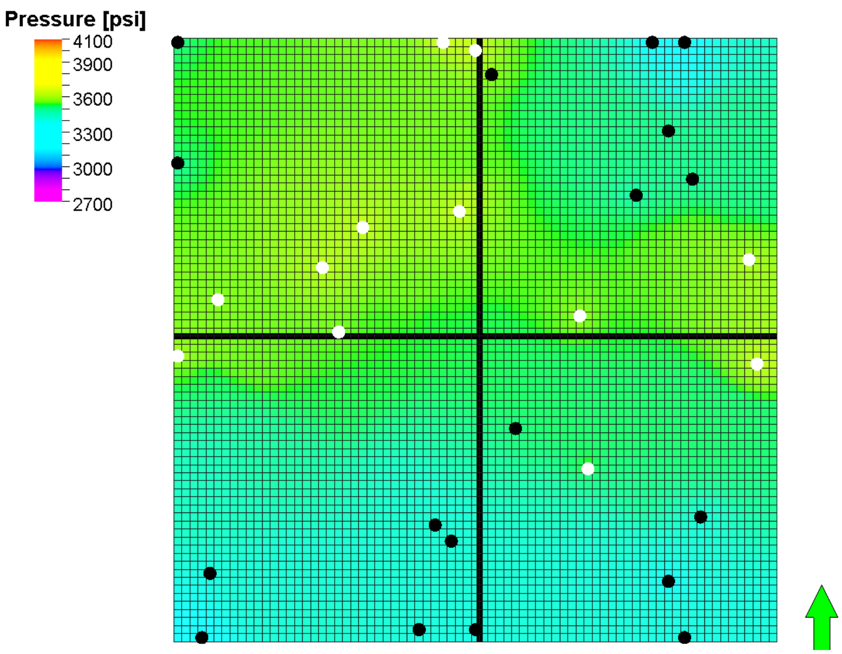

Figure 45: Reservoir average pressure after 30 years for Case 3 (Model 1). Black circles represent producers and white circles represent injectors.

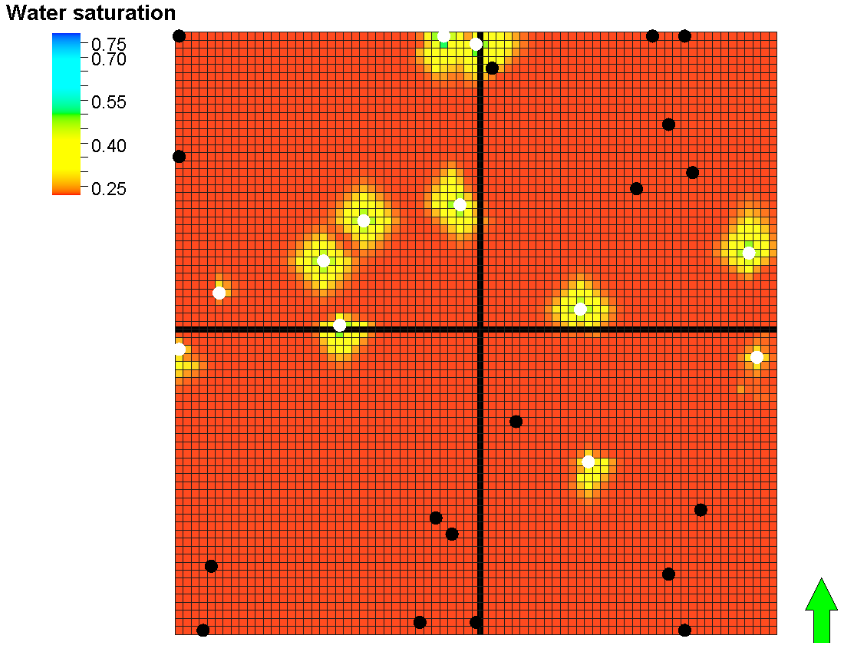

Figure 46: Reservoir water saturation after one year for Case 3 (Model 1). Black circles represent producers and white circles represent injectors.

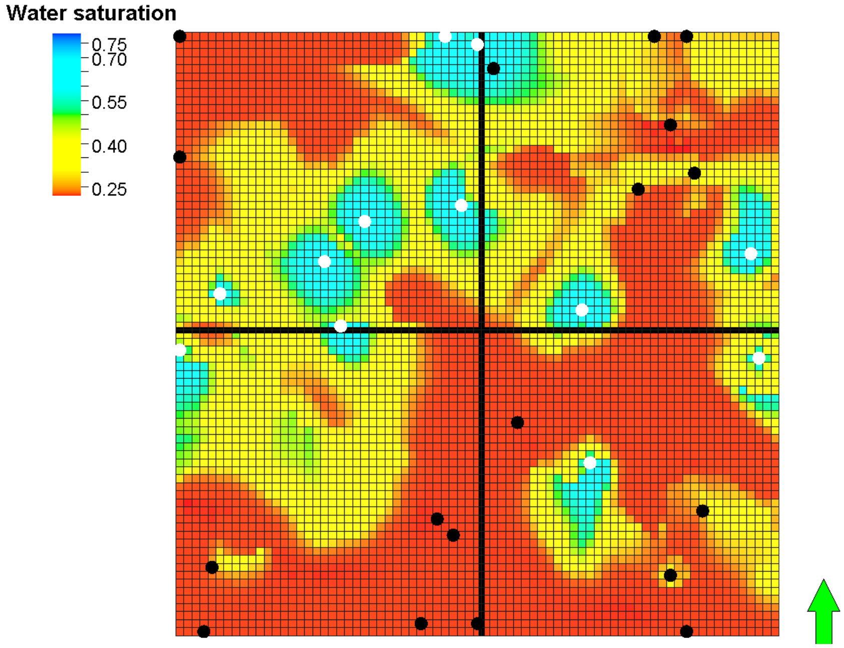

Figure 47: Reservoir water saturation after 30 years for Case 3 (Model 1). Black circles represent producers and white circles represent injectors.

6.4.5 Summary of Results for Model 1

The results of the evaluated cases for Model 1 are summarized in **Table 2**. Results show that the best NPV is that for optimization of NPV alone. When well locations are optimized based on an unconstrained objective function for NPV only, 7.78×10^9 is recorded as the highest NPV among the evaluated cases. However, the cost of that high NPV is an increase in both ΔP and ΔP_r which is undesirable. NPV optimization case is followed by other two cases which try to balance both ΔP and ΔP_r. NPV and P_r balance optimization case reduces ΔP_r from 338.93 psig to 81.85 psig. The reduction results after considering another constraint for regional pressure difference in the objective function. Finally, the final case balances three constraints; NPV, regional average pressure, and reservoir average pressure. NPV of 7.25×10^9 is recorded in this case which is better than NPV values recorded for the pattern cases. Both regional average pressure and reservoir average pressure are also maintained.

Table 2: Results summary for Model 1

Case	NPV	ΔP_r		ΔP	
		Max ΔP_r	Final ΔP_r	Max ΔP	Final ΔP
Pattern 1	7.11×10^9	60.90	47.08	1151	1137
Pattern 2	6.93×10^9	56.90	47.34	1180	1180
Pattern 3	7.04×10^9	15.93	14.18	568	387
Case 1	7.78×10^9	338.93	310.21	1761	1736
Case 2	7.53×10^9	81.85	77.14	1819	1812
Case 3	7.25×10^9	91.39	90.12	741	529

6.5 Model 2 ($64 \times 64 \times 3$)

The previous study in Model 1 was repeated on another model to ensure capturing the same behavior. A reservoir model of 12,288 cells was used in the following scenarios for optimizing NPV and regional pressure balance. The reservoir is discretized into $64 \times 64 \times 3$ grid cells. The model is a two-phase oil and water system. Similar to Model 1, four regions were defined in each scenario to evaluate regional pressure difference between all the cases. The reservoir was divided into four equal regions. The number of wells in this model is 30 where 18 of them are producers and the other 12 are injectors. The number of simulation years was set to 30 where each simulation run starts on October 2011 and ends on October 2041. Grid cell size is $200 \times 200 \times 100$ and the reservoir is heterogeneous. Production rate was set to 1500 b/d on all producers and the minimum bottomhole pressure in producers was set to 2000 psig. Injection rate was set to 2500 b/d on all injectors and the maximum bottomhole pressure in injectors was set to 6500 psig. **Figure 48** presents permeability distribution (in mD) of this heterogeneous reservoir. The porosity of layer 1, layer 2, and layer 3 is 0.23, 0.17, and 0.11, respectively.

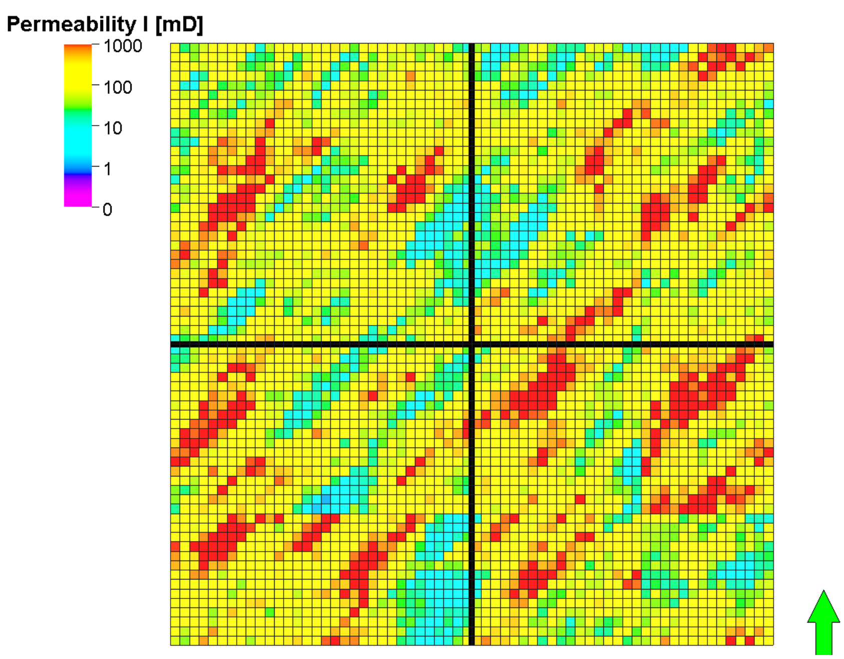

Figure 48: Permeability distribution of Model 2 (Heterogeneous reservoir)

6.5.1 Well Location Patterns

As done in Model 1 cases, three different well distribution patterns were evaluated in Model 2 to compare their results with the optimization cases. The results from these well patterns were considered as the base for evaluating the proposed multi-objective optimization and for coming up with decisions when looking at results. Note that no well optimization was carried out on these pattern cases.

Pattern 1

The first pattern in Model 2 presented in **Figure 49** distributes wells by alternating producers and injectors columns. Some producers and injectors are placed very close to the borders of the regions which might result in major contribution of these wells in more than one region.

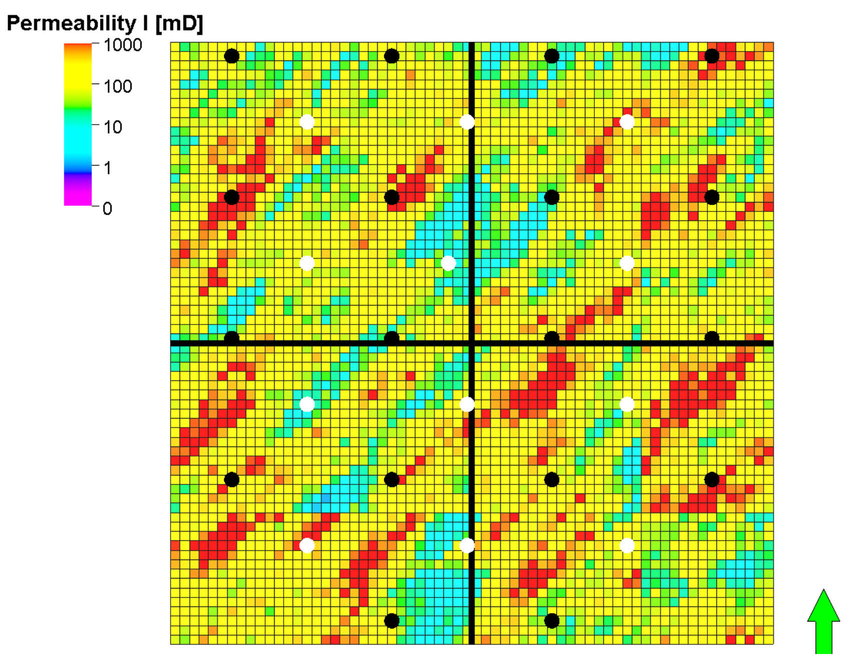

Figure 49: Well distribution of Pattern 1 (Model 2). Black circles represent producers and white circles represent injectors.

Having this well distribution pattern, the model resulted in an NPV of 6.07×10^{9} after 30 years. Reservoir average pressure drops from 4000 psig to 3370 psig and then increases to 3770 psig during 30 years (See **Figure 50**).

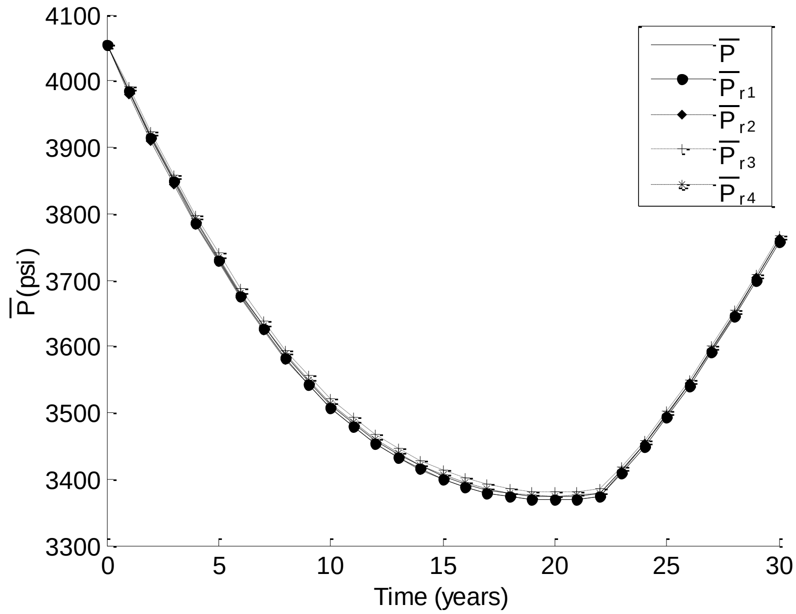

Figure 50: Regional average pressure for Pattern 1 case (Model 2)

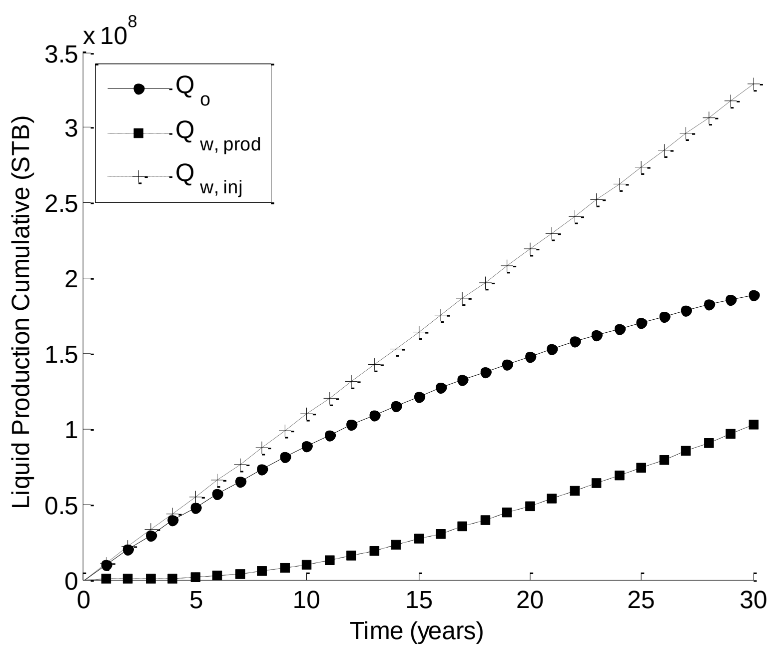

Figure 51: Liquid production cumulative curves for Pattern 1 case (Model 2)

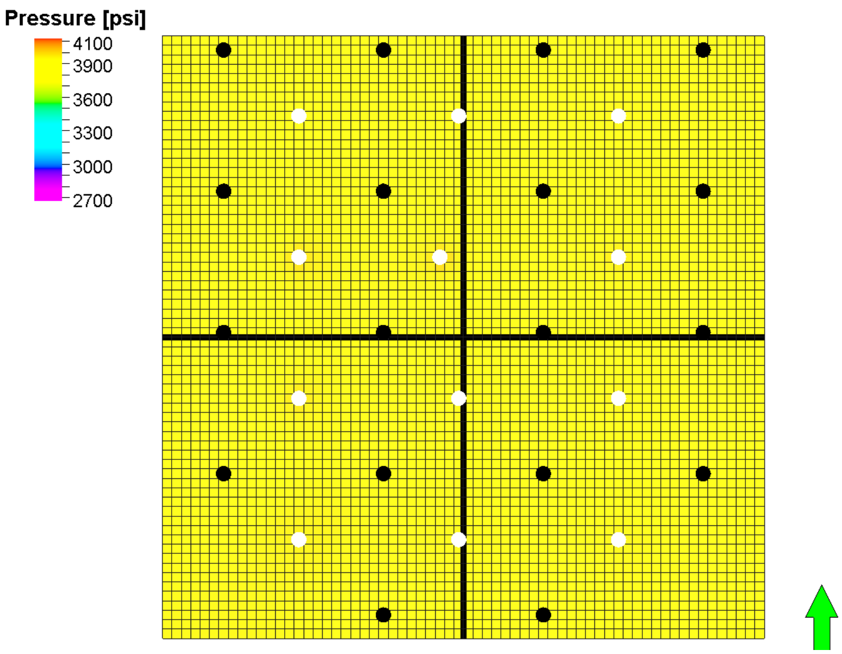

Figure 52: Reservoir average pressure after one year for Pattern 1 (Model 2). Black circles represent producers and white circles represent injectors.

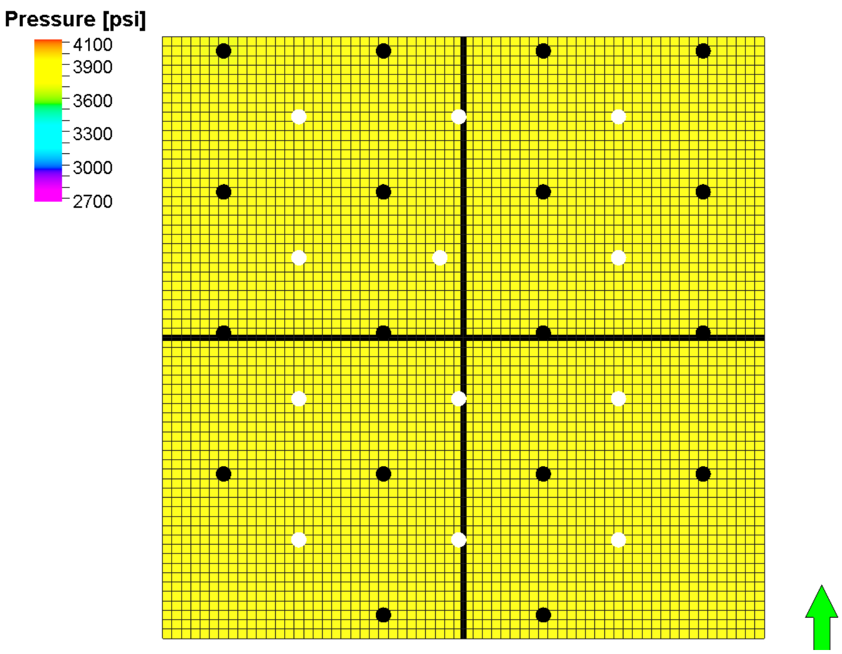

Figure 53: Reservoir average pressure after 30 years for Pattern 1 (Model 2). Black circles represent producers and white circles represent injectors.

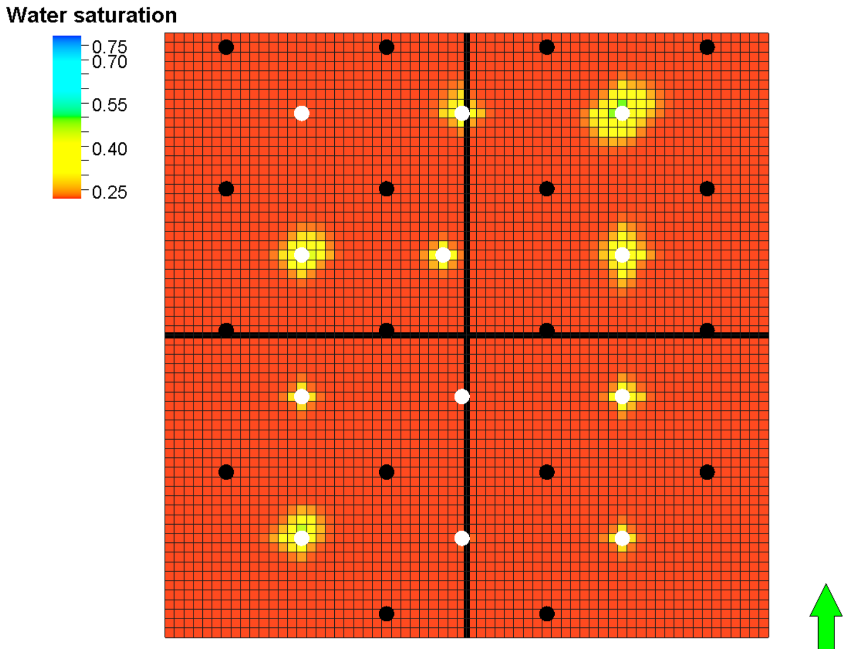

Figure 54: Reservoir water saturation after one year for Pattern 1 (Model 2). Black circles represent producers and white circles represent injectors.

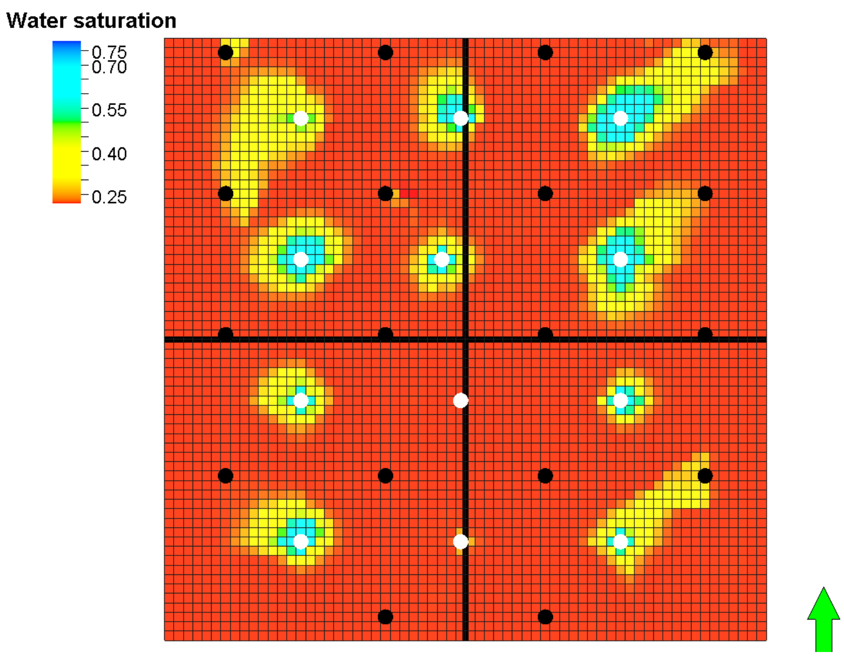

Figure 55: Reservoir water saturation after 30 years for Pattern 1 (Model 2). Black circles represent producers and white circles represent injectors.

Pattern 2

The second pattern presented in **Figure 56** distributes wells by placing the injectors at the edges of the model whereas the producers are placed in the middle. Some producers are placed very close to the borders of the regions which might result in major contribution of these wells in more than one region.

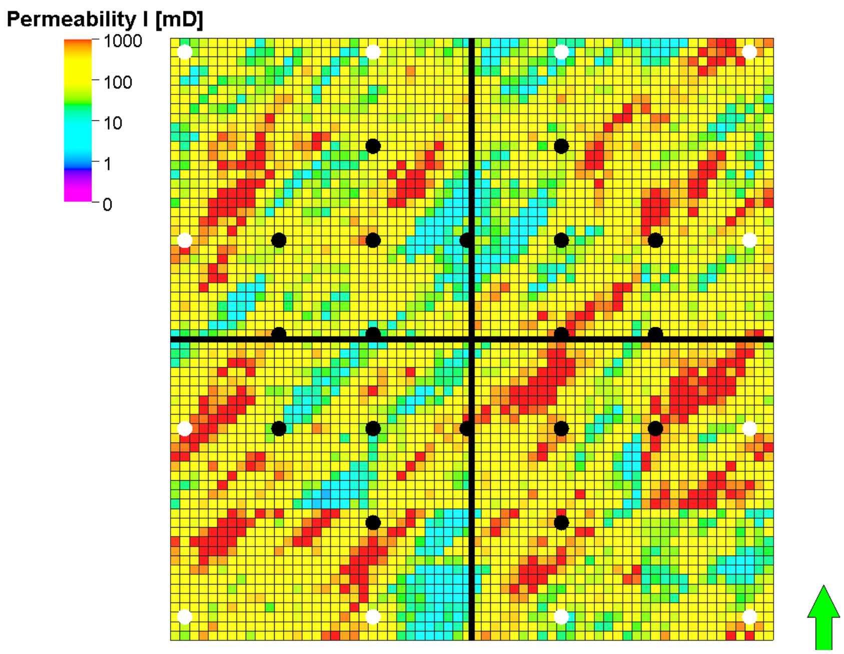

Figure 56: Well distribution of Pattern 2 (Model 2). Black circles represent producers and white circles represent injectors.

Having this well distribution pattern, the model resulted in an NPV of 6.34×10^{9} after 30 years. Reservoir average pressure drops from 4000 psig to 3300 psig during 30 years (See **Figure 57**).

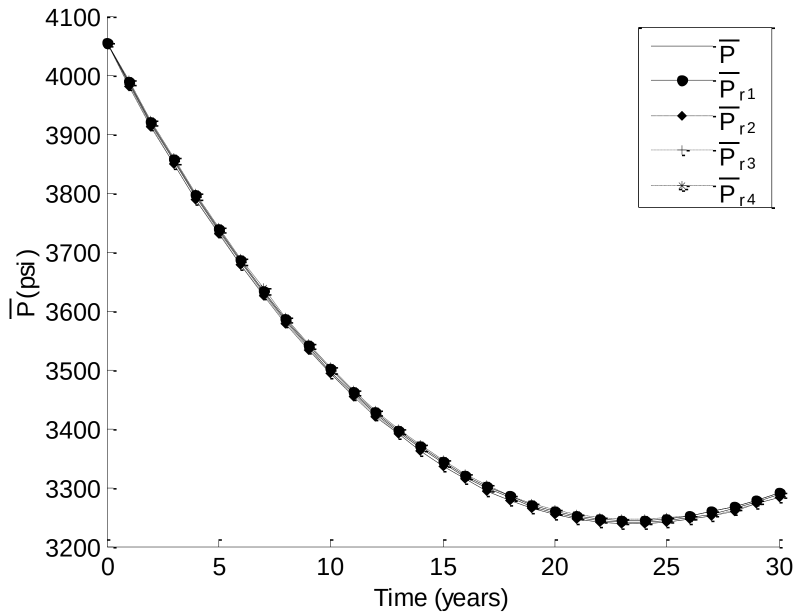

Figure 57: Regional average pressure for Pattern 2 case (Model 2)

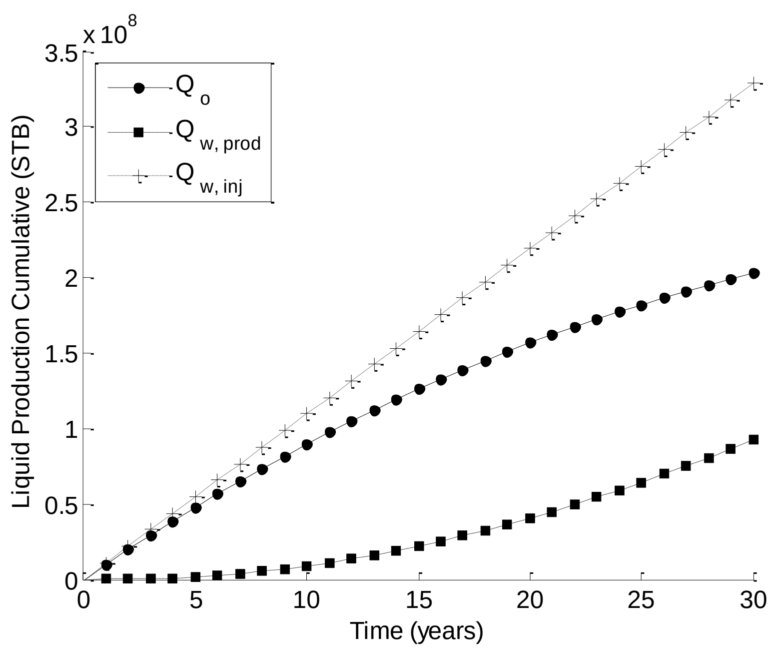

Figure 58: Liquid production cumulative curves for Pattern 2 case (Model 2)

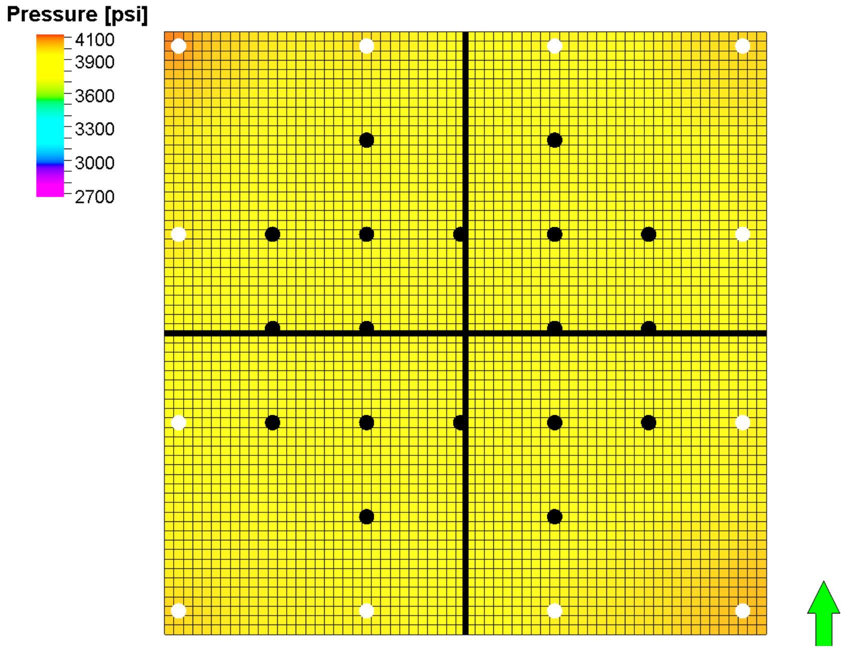

Figure 59: Reservoir average pressure after one year for Pattern 2 (Model 2). Black circles represent producers and white circles represent injectors.

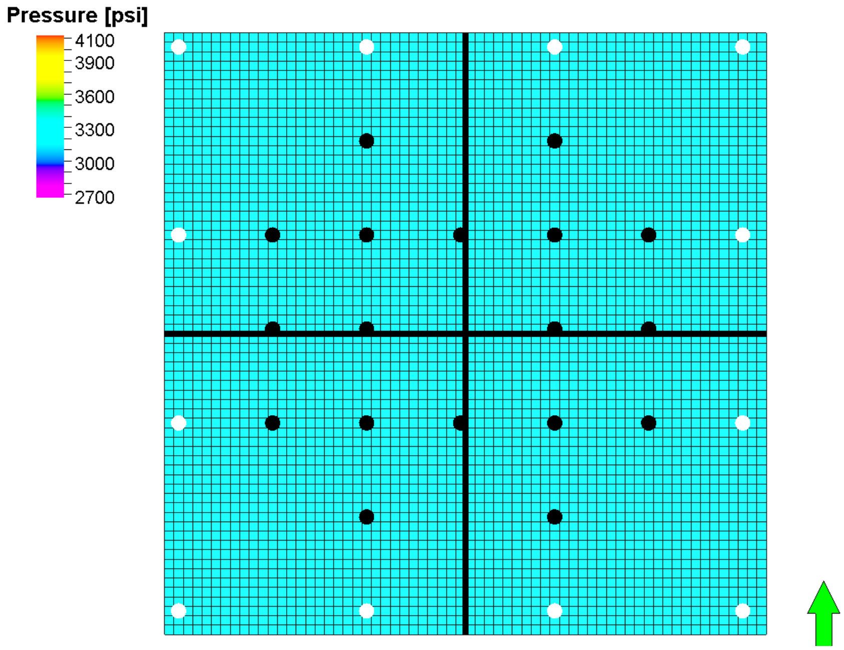

Figure 60: Reservoir average pressure after 30 years for Pattern 2 (Model 2). Black circles represent producers and white circles represent injectors.

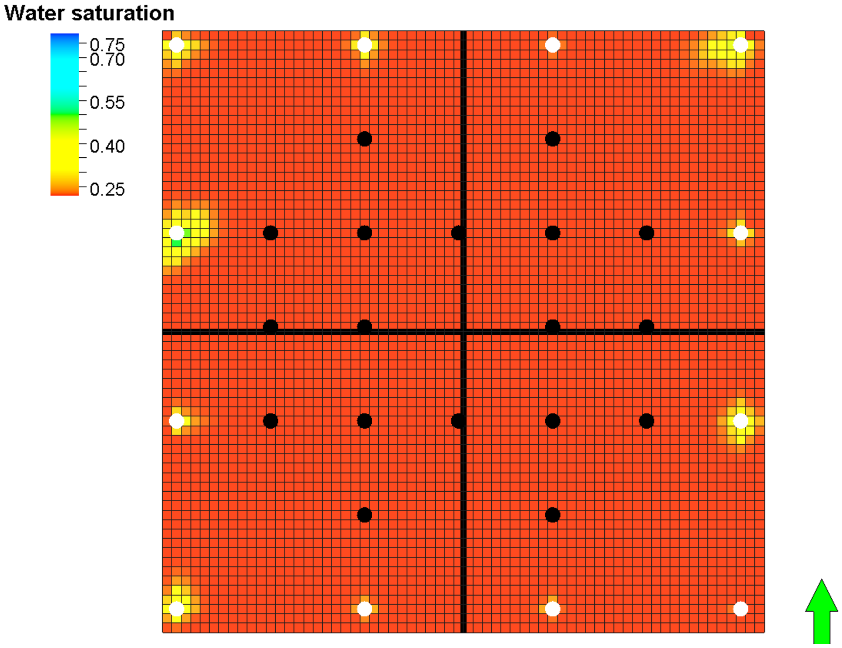

Figure 61: Reservoir water saturation after one year for Pattern 2 (Model 2). Black circles represent producers and white circles represent injectors.

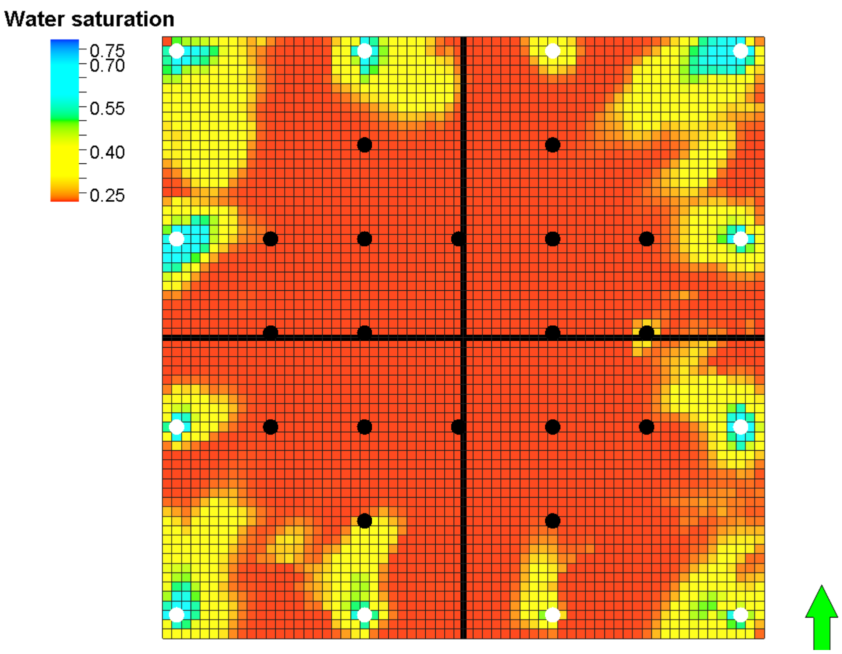

Figure 62: Reservoir water saturation after 30 years for Pattern 2 (Model 2). Black circles represent producers and white circles represent injectors.

Pattern 3

The third pattern presented in **Figure 63** distributes wells by alternating producers and injectors columns. Wells are distributed in a way similar to that in Pattern 1, but with small difference. Some producers and injectors are placed very close to the borders of the regions which might result in major contribution of these wells in more than one region.

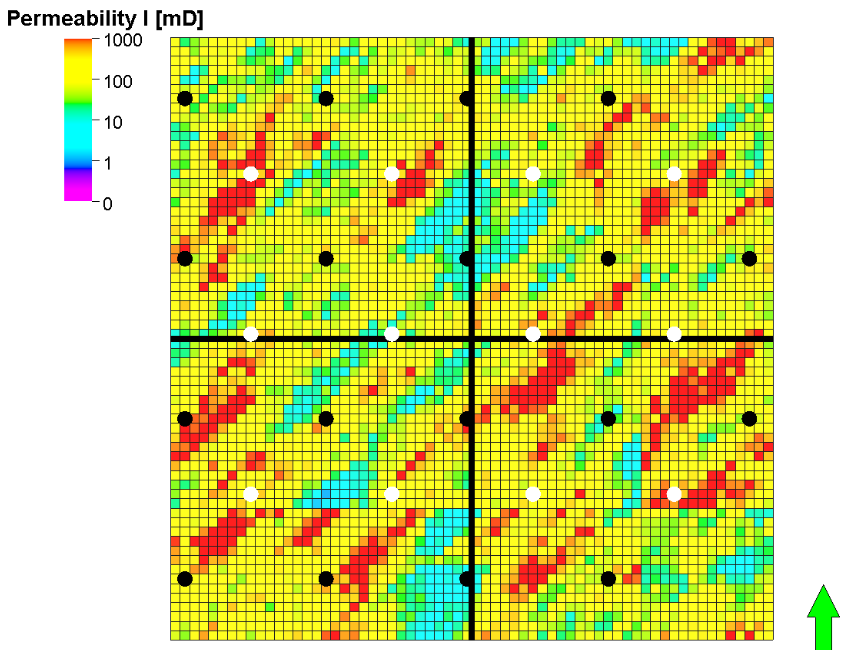

Figure 63: Well distribution of Pattern 3 (Model 2). Black circles represent producers and white circles represent injectors.

The above well distribution pattern resulted in an NPV of 7.34×10^{9} after 30 years. Reservoir average pressure drops from 4000 psig to 3300 psig and then increases to 3400 psig during 30 years (See **Figure 64**).

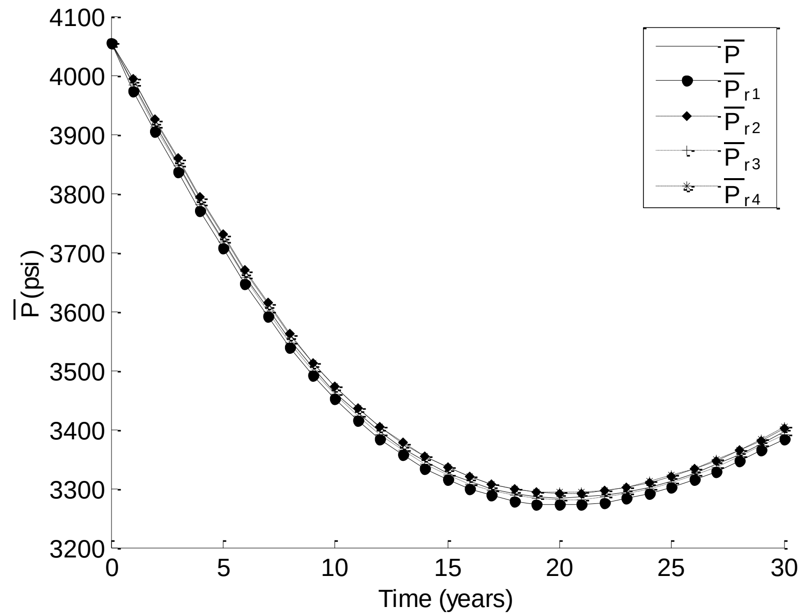

Figure 64: Regional average pressure for Pattern 3 case (Model 2)

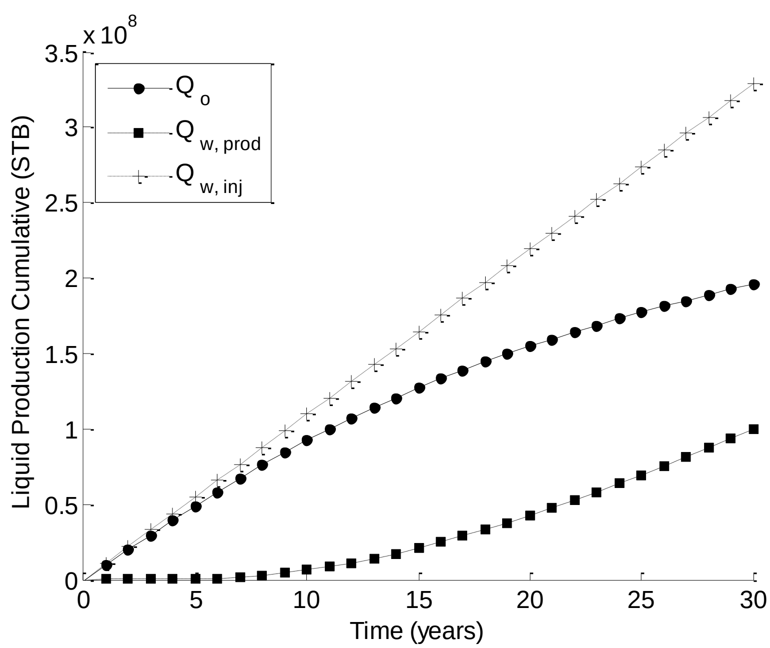

Figure 65: Liquid production cumulative curves for Pattern 3 case (Model 2)

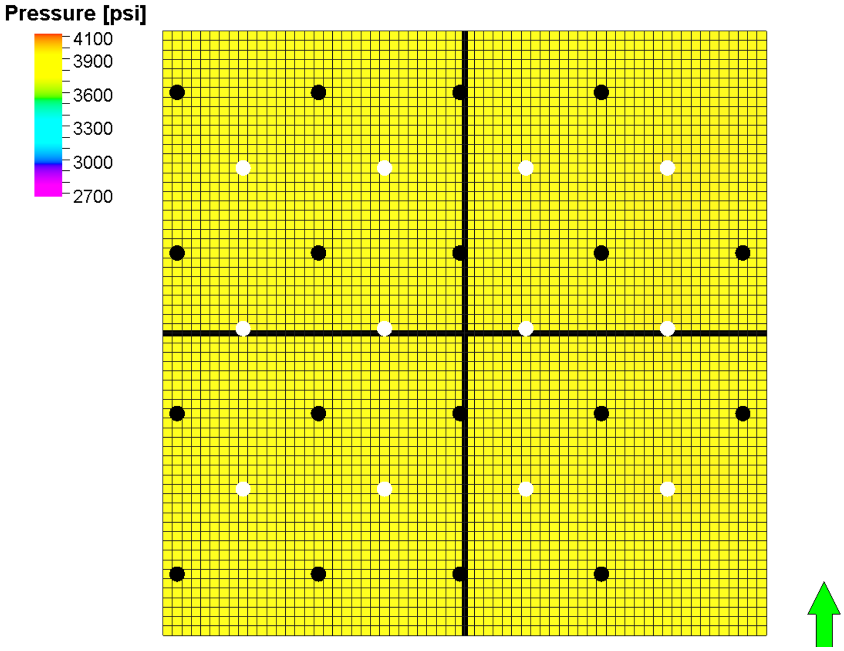

Figure 66: Reservoir average pressure after one year for Pattern 3 (Model 2). Black circles represent producers and white circles represent injectors.

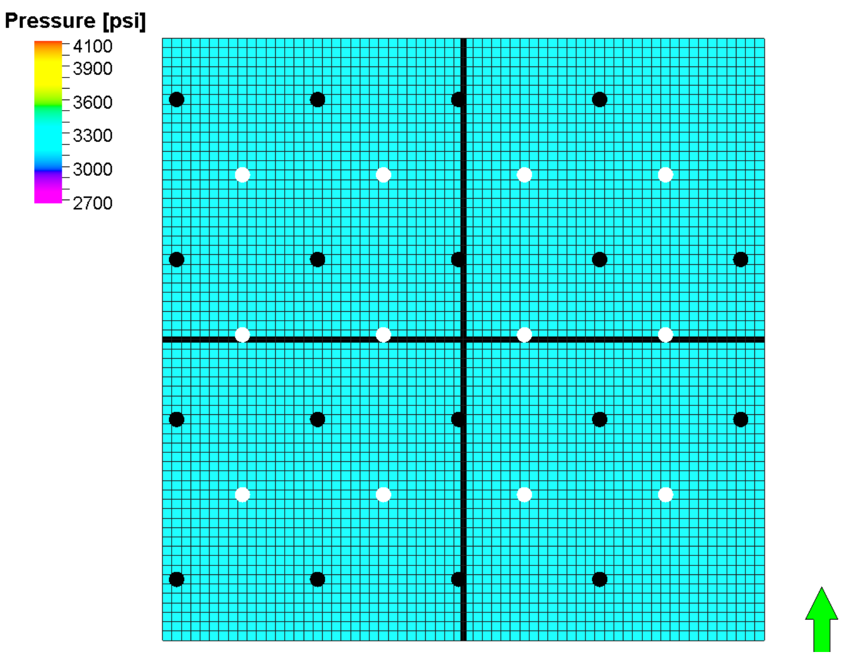

Figure 67: Reservoir average pressure after 30 years for Pattern 3 (Model 2). Black circles represent producers and white circles represent injectors.

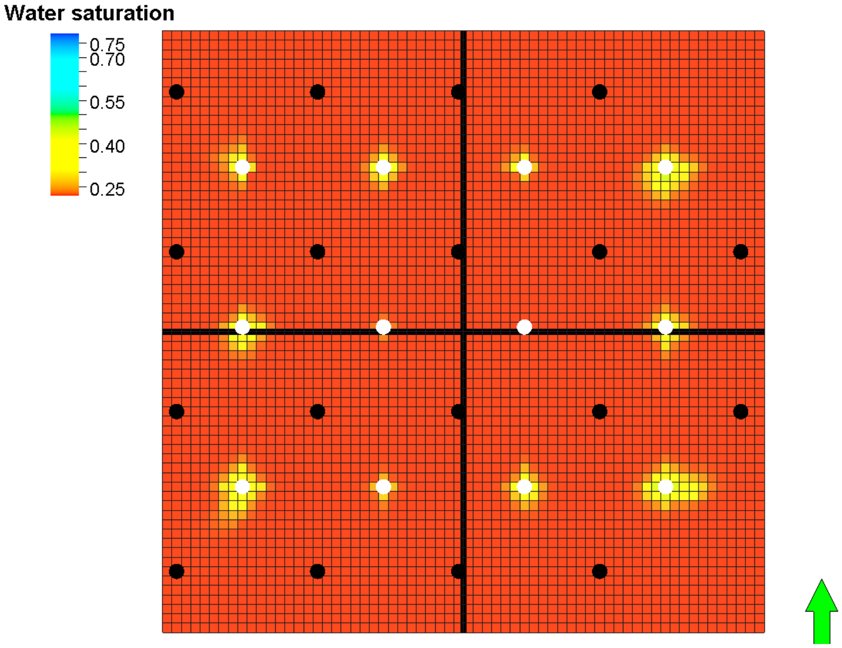

Figure 68: Reservoir water saturation after one year for Pattern 3 (Model 2). Black circles represent producers and white circles represent injectors.

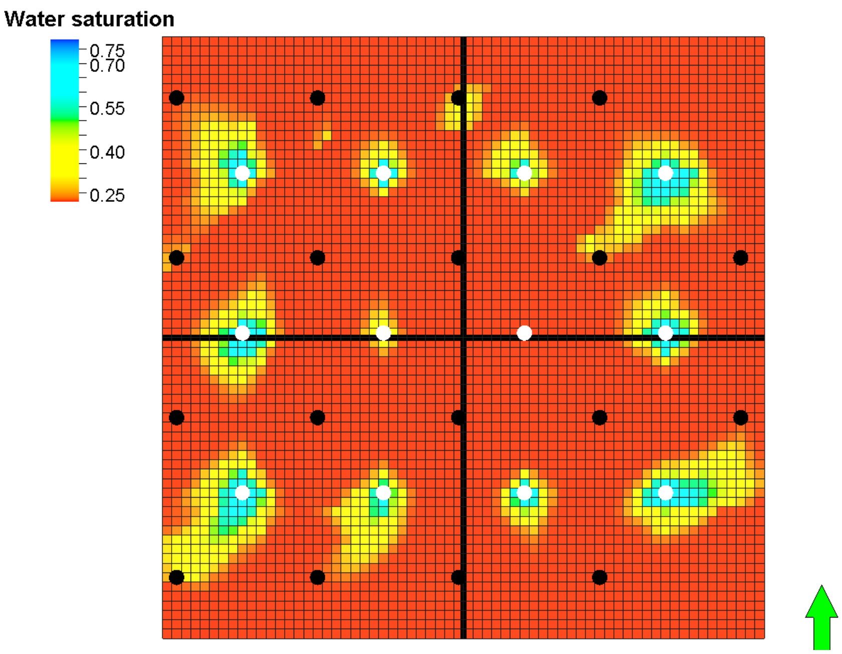

Figure 69: Reservoir water saturation after 30 years for Pattern 3 (Model 2). Black circles represent producers and white circles represent injectors.

6.5.2 Case 1: Optimization of NPV Alone

In optimization of NPV only, the focus is to increase NPV only without giving attention to regional pressure balance. Basically, the objective function in this case is:

$$\Phi_{NPV,\kappa} = -NPV_{\kappa} \quad (13)$$

This objective function is an unconstrained objective function since it takes care of one objective only with no constraints. This optimization resulted in the well distribution shown in **Figure 70**. The resultant well distribution results in an NPV of 7.18×10^{9} after 30 years. As expected, NPV in this case is higher than those for the evaluated well pattern cases. However, reservoir average pressure drops from 4000 psig to 2850 psig during 30 years (See **Figure 71**) which results in ΔP of 1150 psig which is higher than ΔP of the well pattern cases (600 psig, 700 psig, 700 psig). This pressure drop is expected since the optimization focuses on NPV only without looking at reservoir pressure. Moreover, regional pressure is affected where a difference of 180 psig is noted between $\overline{P}_{r1}$ and $\overline{P}_{r2}$. Note also that some producers and injectors are very close to each other and there is no balance in well locations among all regions.

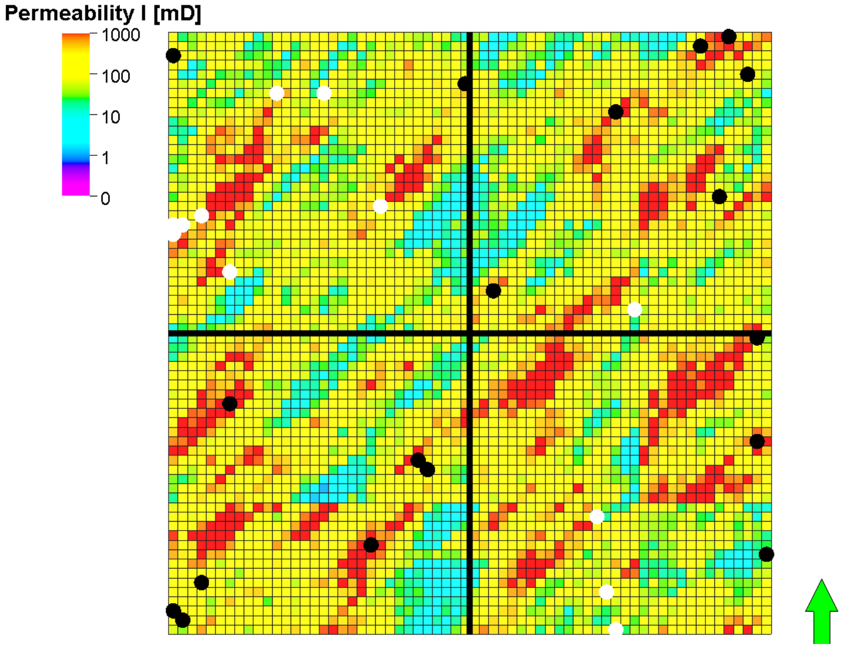

Figure 70: Well distribution of Case 1 (Model 2). Black circles represent producers and white circles represent injectors.

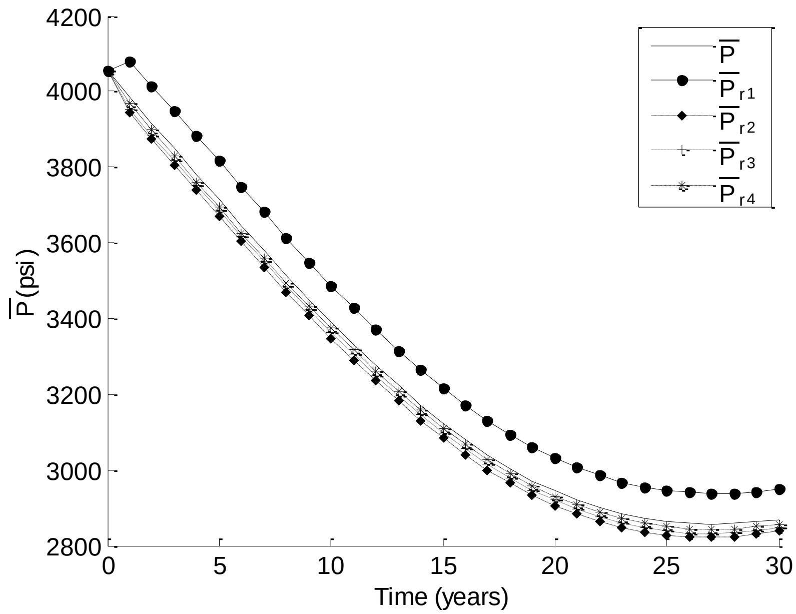

Figure 71: Regional average pressure for Case 1 (Model 2)

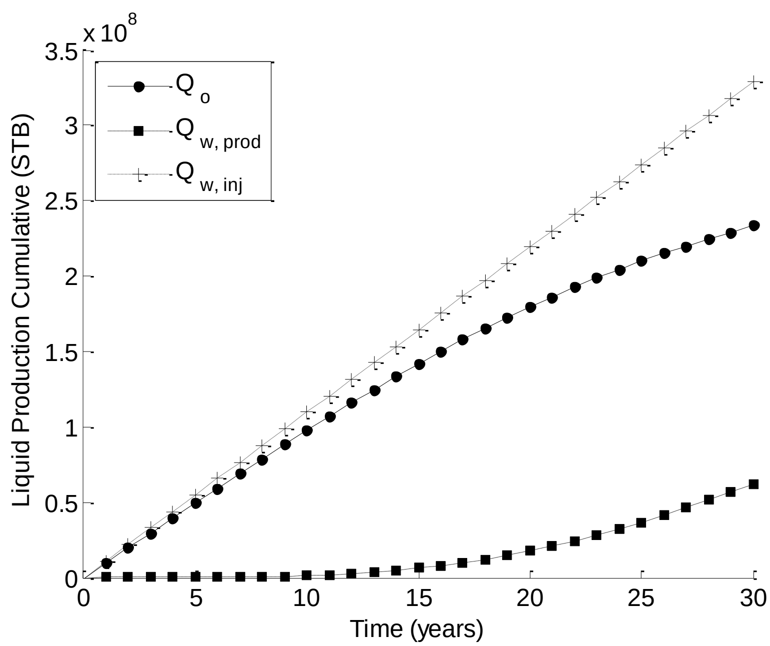

Figure 72: Liquid production cumulative curves for Case 1 (Model 2)

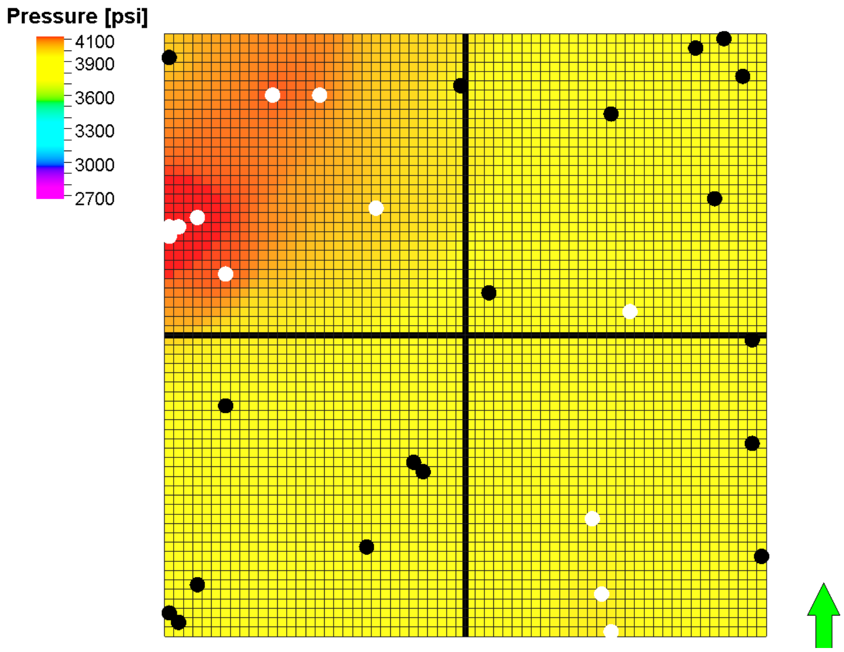

Figure 73: Reservoir average pressure after one year for Case 1 (Model 2). Black circles represent producers and white circles represent injectors.

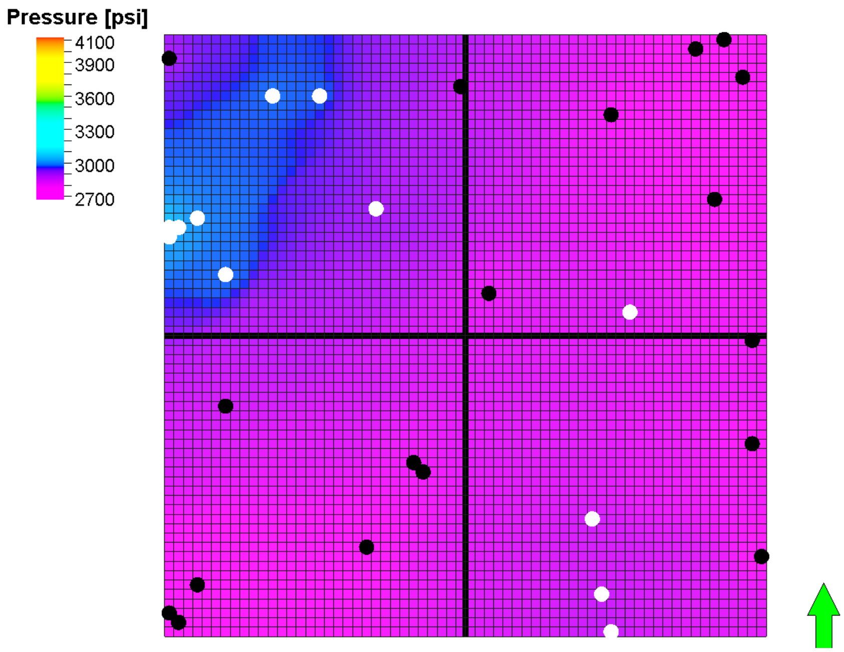

Figure 74: Reservoir average pressure after 30 years for Case 1 (Model 2). Black circles represent producers and white circles represent injectors.

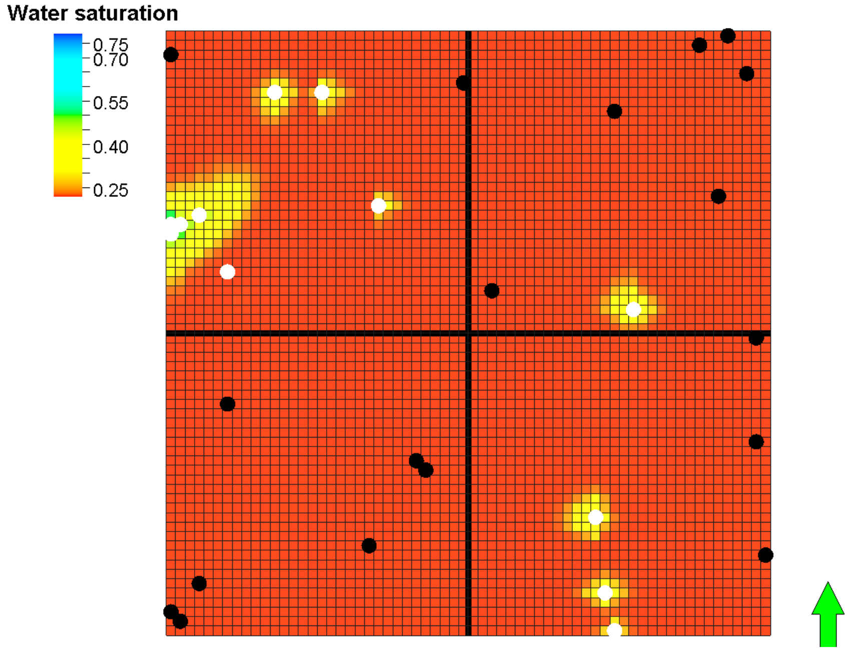

Figure 75: Reservoir water saturation after one year for Case 1 (Model 2). Black circles represent producers and white circles represent injectors.

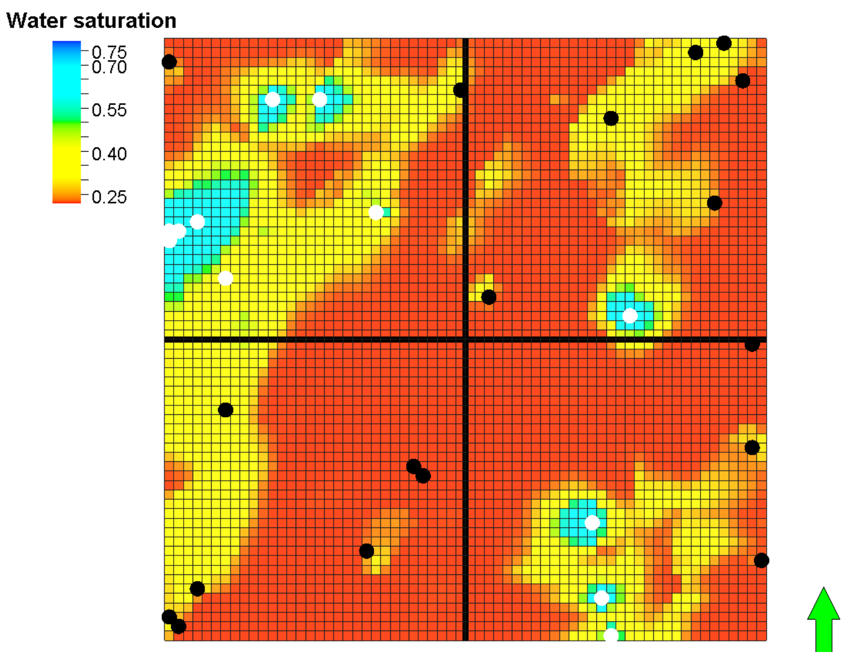

Figure 76: Reservoir water saturation after 30 years for Case 1 (Model 2). Black circles represent producers and white circles represent injectors.

6.5.3 Case 2: Optimization of NPV Subject to Regional Pressure Constraint

In the previous case, well placement was optimized by focusing on NPV only which resulted in large reservoir average pressure drop and in an increase in the difference between regional average pressure values. In this case, the difference between regional average pressure values is included in the optimization function in order to minimize that difference. The objective function becomes now an unconstrained objective function. Below is the objective function used in this case:

$$\Phi_{COF,\kappa} = -NPV_{\kappa} + \sum_{j=1}^{N_c} \dot{\zeta}_{k,j} \left[u_{k,j}\left(\vec{\alpha}\right) \right]^{a} \tag{14}$$

This optimization resulted in the well distribution shown in **Figure 77**. The resultant well distribution results in an NPV of 6.62×10^9 after 30 years. NPV in this case is still higher than those for the evaluated well pattern cases. However, NPV in this case is less than that for NPV optimization case. This reduction in NPV is the cost for adding another objective in the objective function. Reservoir average pressure drops from 4000 psig to 3200 psig during 30 years (See **Figure 78**) which results in ΔP of 800 psig which is higher than ΔP of the well pattern cases (600 psig, 700 psig, 700 psig) and is less than that for NPV optimization case. This pressure drop is expected since the optimization focuses on increasing NPV and minimizing regional pressure only without looking at overall reservoir average pressure. Regional average pressure difference, however, is reduced from 180 psig to 100 psig. Note also that well distribution is balanced among the four regions.

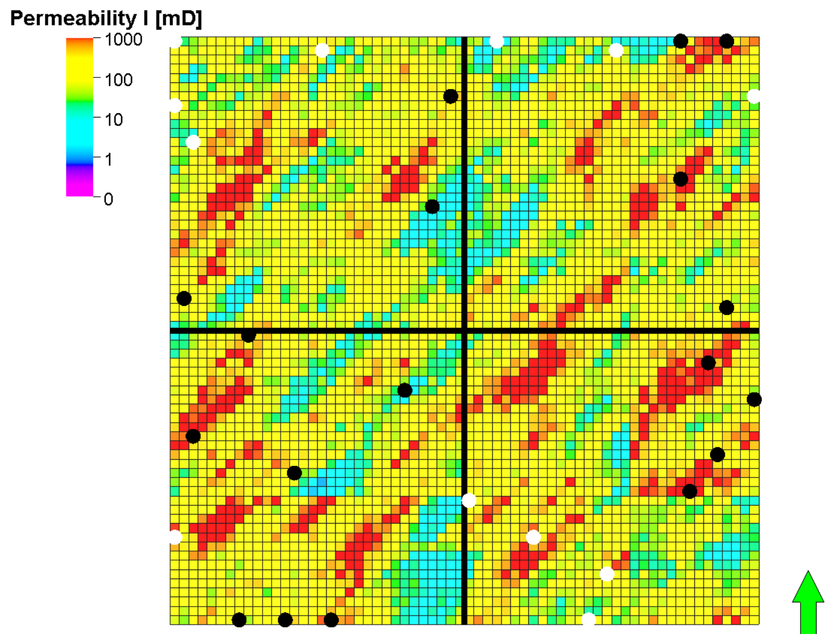

Figure 77: Well distribution of Case 2 (Model 2). Black circles represent producers and white circles represent injectors.

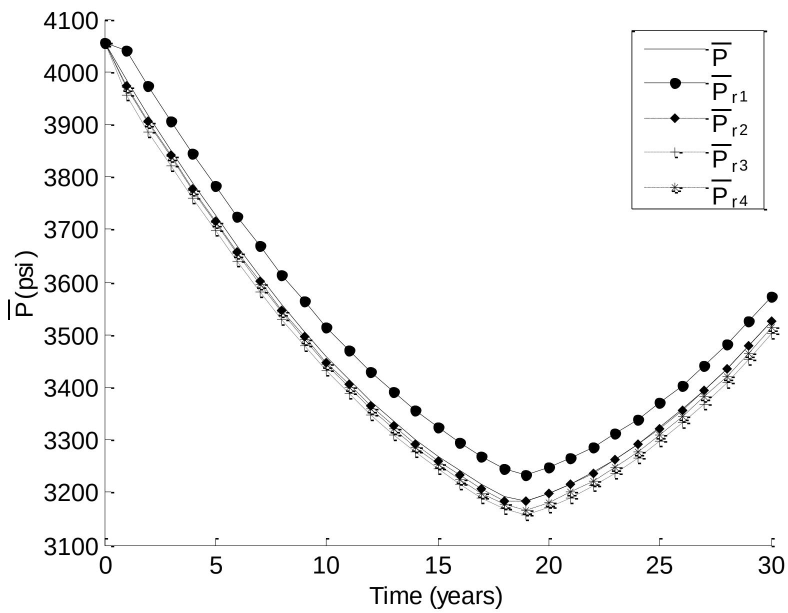

Figure 78: Regional average pressure for Case 2 (Model 2)

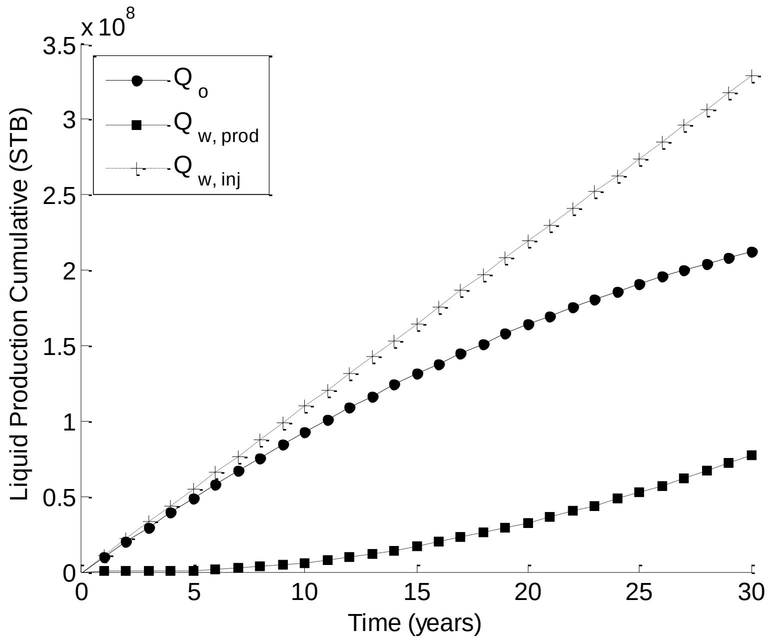

Figure 79: Liquid production cumulative curves for Case 2 (Model 2)

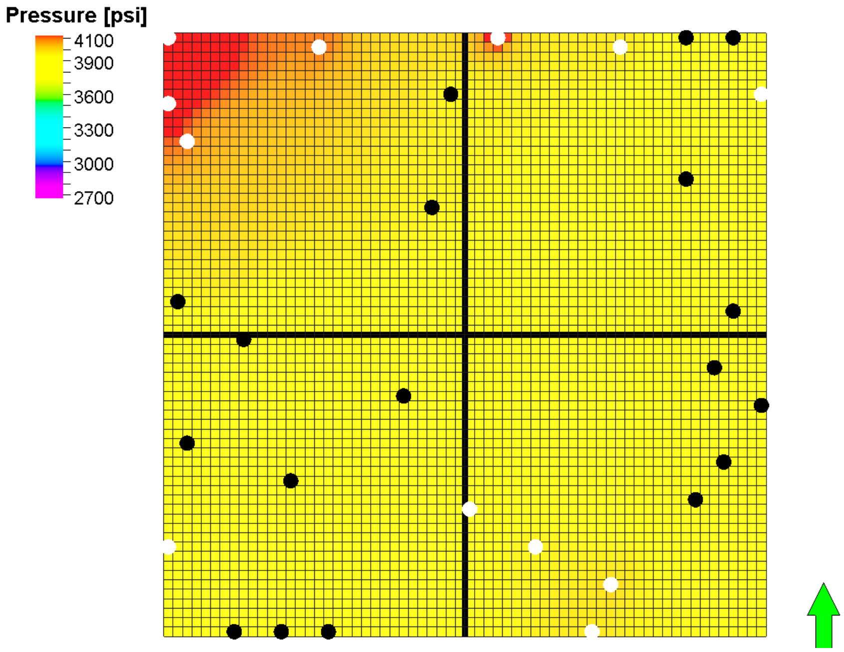

Figure 80: Reservoir average pressure after one year for Case 2 (Model 2). Black circles represent producers and white circles represent injectors.

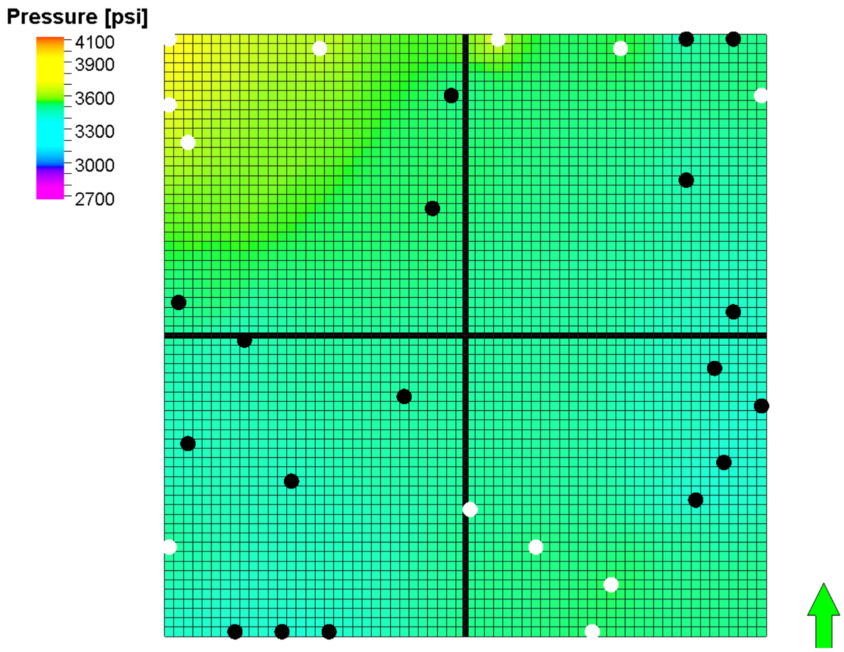

Figure 81: Reservoir average pressure after 30 years for Case 2 (Model 2). Black circles represent producers and white circles represent injectors.

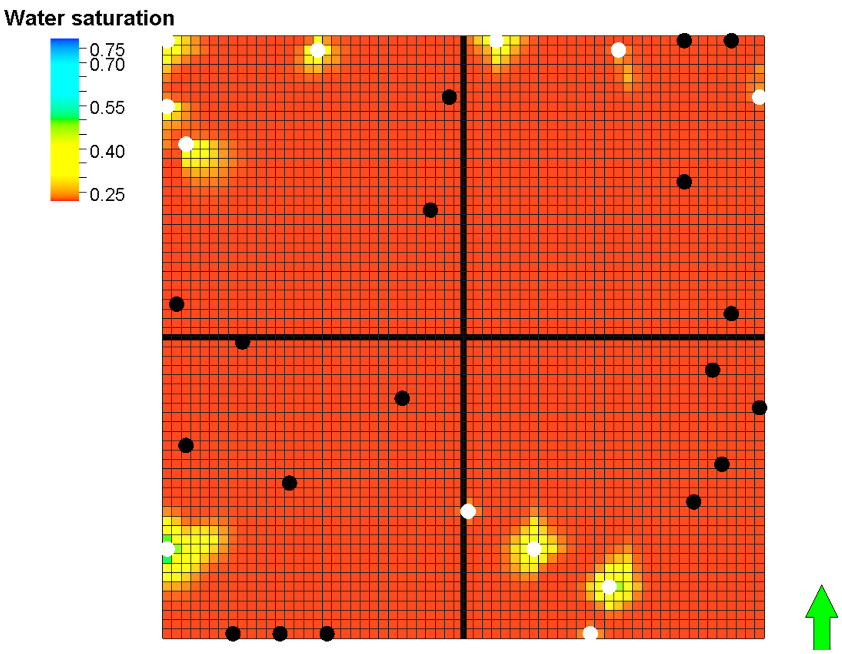

Figure 82: Reservoir water saturation after one year for Case 2 (Model 2). Black circles represent producers and white circles represent injectors.

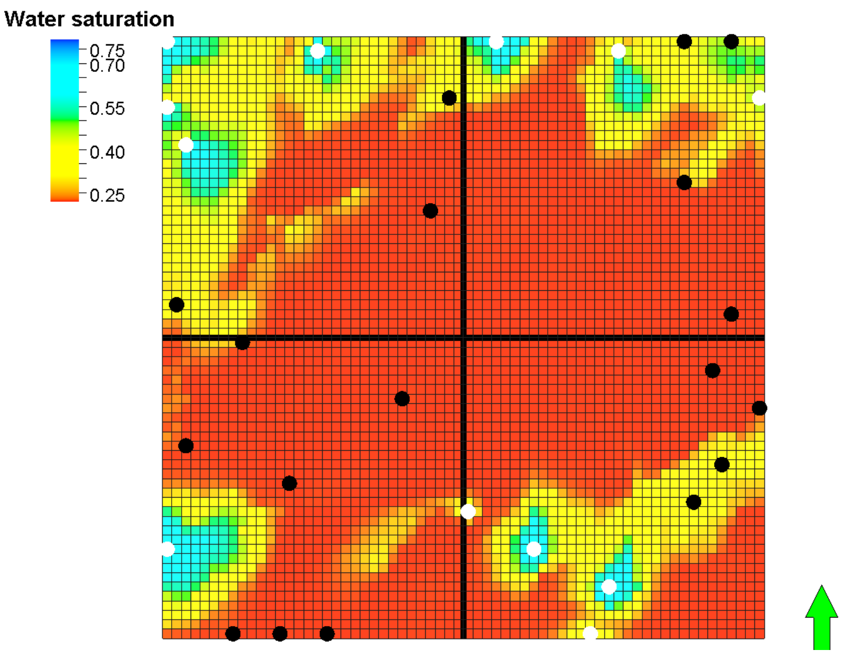

Figure 83: Reservoir water saturation after 30 years for Case 2 (Model 2). Black circles represent producers and white circles represent injectors.

6.5.4 Case 3: Optimization of NPV Subject to Regional Pressure Constraint and Average Reservoir Pressure Constraint

In the previous case, well placement was optimized by increasing NPV and minimizing regional pressure difference only. In that case, the difference between regional average pressure is minimized as desired. However, that case resulted in large reservoir average pressure drop which is similar to that case of NPV optimization. In this case, the difference between reservoir average pressure and reservoir initial pressure is included in the optimization function in order to minimize pressure drop. In this case reservoir average pressure is allowed to drop by 500 psig as maximum. Below is the objective function used in this case:

$$\Phi_{COF,\kappa} = -NPV_{\kappa} + \sum_{j=1}^{N_c} \dot{\zeta}_{k,j} \left[u_{k,j} \left(\vec{\alpha} \right) \right]^a + \sum_{j=1}^{N_c} \dot{\zeta}_{k,j} \left[v_{k,j} \left(\vec{\alpha} \right) \right]^a \qquad (15)$$

This optimization resulted in the well distribution shown in **Figure 84**. The resultant well distribution results in an NPV of 6.61×10^9 after 30 years. NPV in this case is still higher than those for the evaluated well pattern cases. However, NPV in this case is less than those for NPV optimization and the constrained optimization cases. As seen in the previous case, as we add more constraints to the objective function, NPV gets reduced. Reservoir average pressure drops from 4000 psig to 3520 psig and then increases to 3720 psig during 30 years (See **Figure 85**) which results in maximum ΔP of 480 psig which is less than ΔP of those all previous cases. Regional average pressure difference 200 psig in this case.

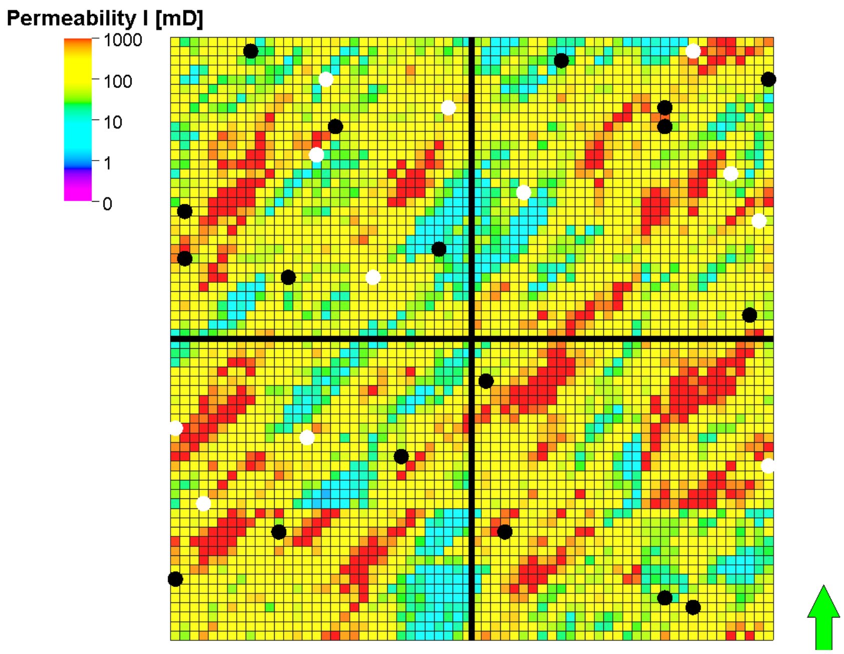

Figure 84: Well distribution of Case 3 (Model 2). Black circles represent producers and white circles represent injectors.

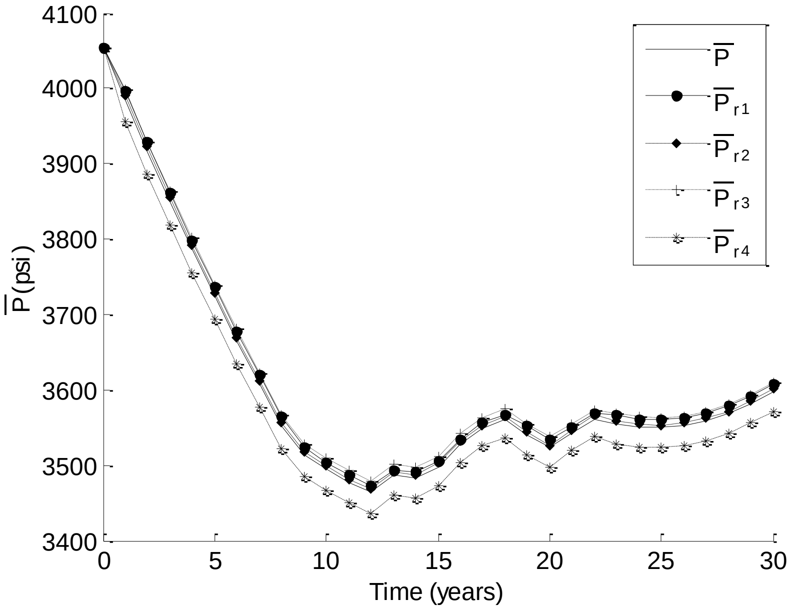

Figure 85: Regional average pressure for Case 3 (Model 2)

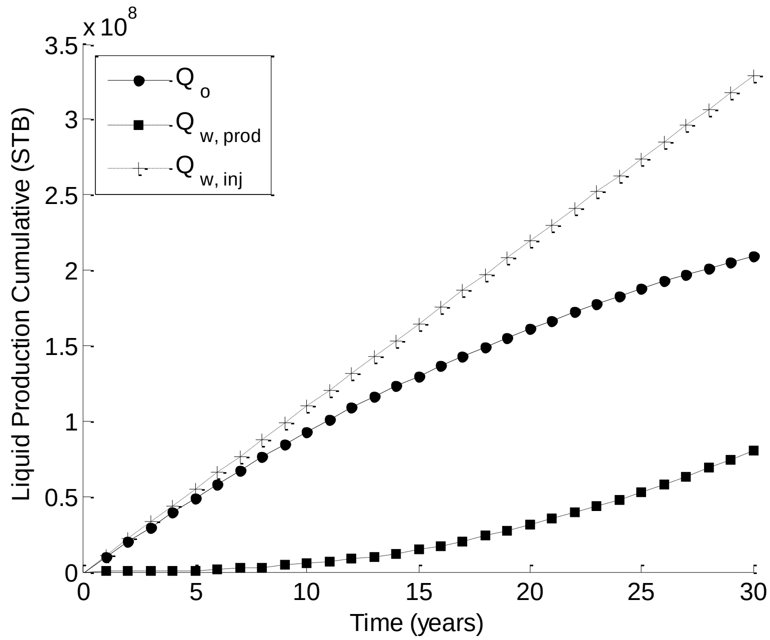

Figure 86: Liquid production cumulative curves for Case 3 (Model 2)

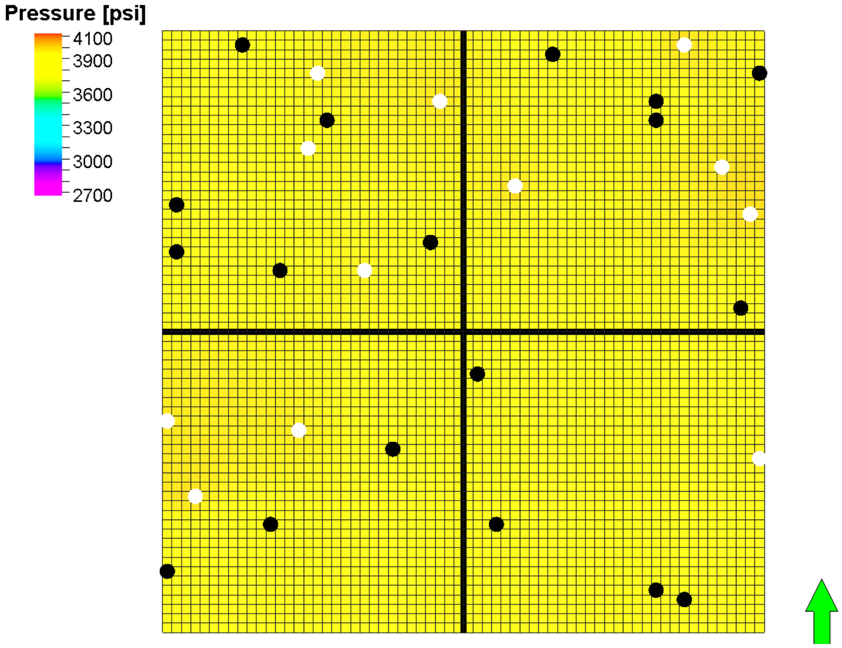

Figure 87: Reservoir average pressure after one year for Case 3 (Model 2). Black circles represent producers and white circles represent injectors.

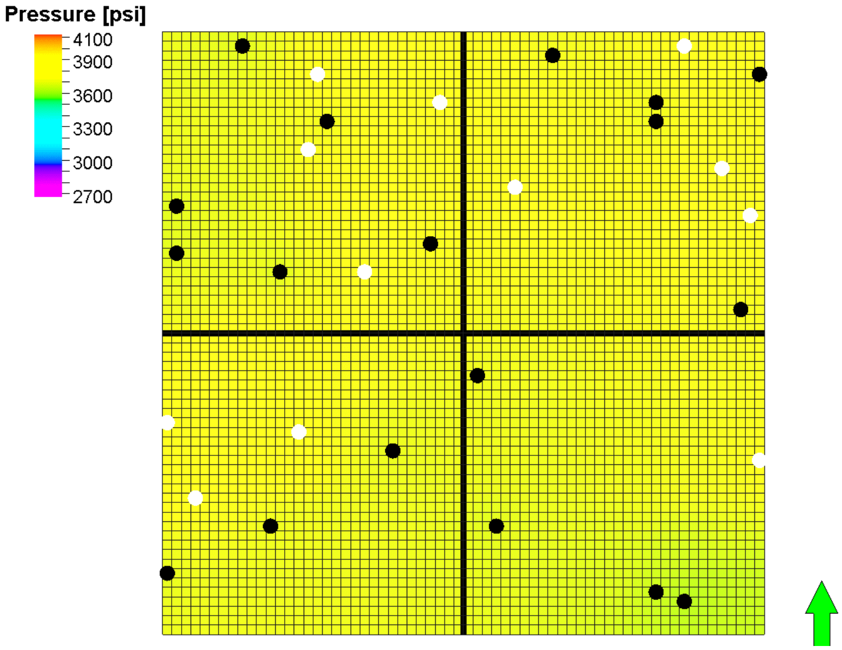

Figure 88: Reservoir average pressure after 30 years for Case 3 (Model 2). Black circles represent producers and white circles represent injectors.

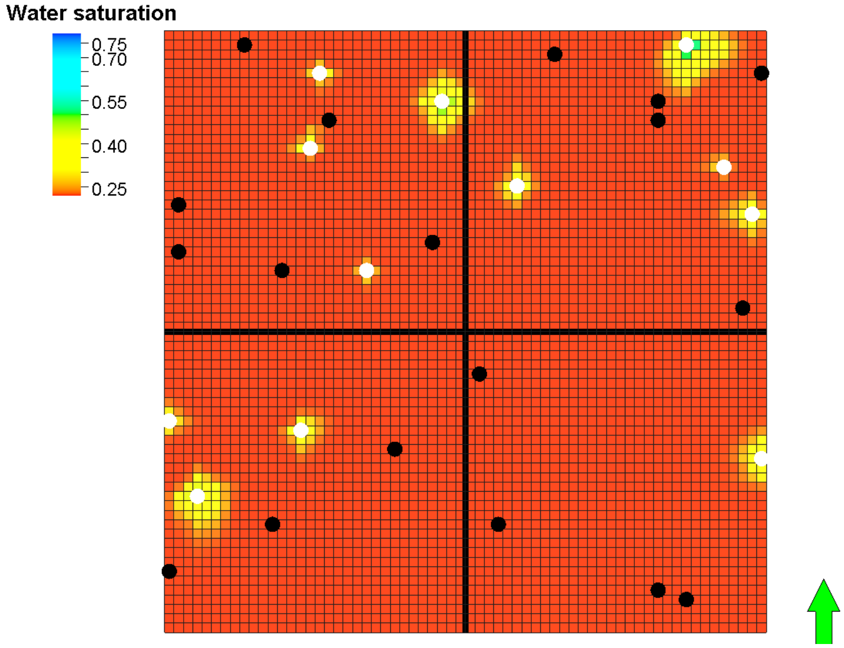

Figure 89: Reservoir water saturation after one year for Case 3 (Model 2). Black circles represent producers and white circles represent injectors.

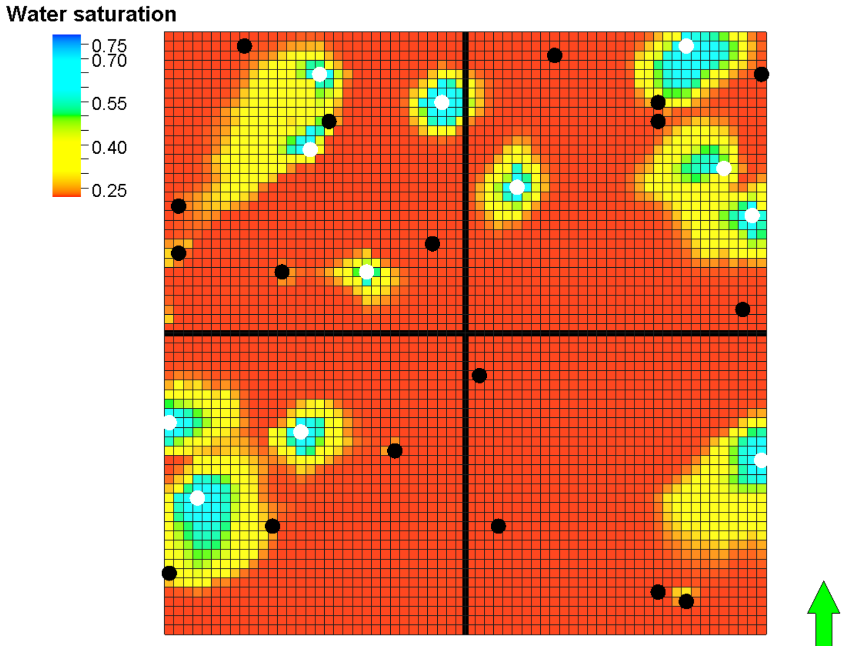

Figure 90: Reservoir water saturation after 30 years for Case 3 (Model 2). Black circles represent producers and white circles represent injectors.

6.5.5 Result Summary for Model 2

The results of the evaluated cases for Model 2 are summarized in **Table 3** below. Results show that the best NPV is that for optimization of NPV only case. When wells locations were optimized based on an unconstrained objective function for NPV only, 7.18×10^{9} is recorded as the highest NPV among the evaluated cases. However, the cost of that high NPV is an increase in both ΔP and ΔP_r which is undesirable. Optimization of NPV only case was followed by other two cases which try to balance both ΔP and ΔP_r. The second case reduced ΔP_r from 144.82 psig to 85.76 psig. The reduction occurred after considering another constraint for regional pressure difference in the objective function. Finally, the last case balances NPV, regional average pressure, and reservoir average pressure. NPV of 6.61×10^{9} was recorded in this case which is better than NPV values recorded for the pattern cases. Both regional average pressure and reservoir average pressure were also maintained.

Table 3: Results summary for Model 2

Case	NPV	ΔP_r		ΔP	
		Max ΔP_r	Final ΔP_r	Max ΔP	Final ΔP
Pattern 1	6.07×10^{9}	13.92	9.02	681	292
Pattern 2	6.34×10^{9}	11.01	7.08	813	767
Pattern 3	6.34×10^{9}	23.04	19.52	770	660
Case 1	7.18×10^{9}	144.82	111.13	1198	1185
Case 2	6.62×10^{9}	85.76	70.72	871	528
Case 3	6.56×10^{9}	45.94	38.01	590	457

CHAPTER 7: SUMMARY AND CONCLUSION

7.1 SUMMARY

The relationship between engineering and geological variables affecting reservoir performance is not simple. Therefore, the determination of optimal well locations cannot be done based on intuitive judgment. The study presented in this thesis optimizes well locations in large scale field development and water flooding projects. Several scenarios were assessed in this optimization on two different reservoir models. As observed in these scenarios, it becomes more challenging as more constraints are considered for indicating the level of performance of an optimization workflow. Unconstrained optimization approach was used first to optimize well locations based on NPV only. The aim of course was to increase NPV to the maximum. Gradually, more constraints were included in the objective function making the problem as a constrained optimization approach. In addition to NPV, two important constraints were considered in the study to account for environmental effects. These two objectives are represented by reservoir average pressure ($\bar{P}$) and regional average pressure ($\bar{P}_r$). The approach maintains $\bar{P}$ by minimizing the pressure drop ($\Delta\bar{P}$). Also, this approach balances $\bar{P}_r$ by minimizing the difference between $\bar{P}_r$ of the four regions ($\Delta\bar{P}_r$). Several scenarios were evaluated in two different reservoir models to see the effect of using different objective functions. The result in each scenario has different values of NPV, $\Delta\bar{P}$, $\Delta\bar{P}_r$, and of course different well locations.

As observed in the presented results, depending on only one objective is enough for certain optimization problems. When well placement was optimized based on NPV only, reservoir average pressure dropped drastically and the regional average pressure lost balance. Therefore, a constrained optimization approach was used then to increase NPV, maintain reservoir average and balance regional average pressure through an objective function which combines all constraints. This was done through building an equation of weighted constraints. Therefore, the results can be easily tuned by compromising the importance of either environmental effects or profitability depending on the nature of the requirements and the desired results.

Both reservoir models showed the same behavior when running the optimization approach. For each reservoir model, three base scenarios were evaluated by pre-locating wells in the reservoir using well patterns. The results of these scenarios were then compared with the results of the optimization approach. The optimization approach was applied on three scenarios; Optimization of NPV only, optimization of NPV subject to regional pressure constraint, and optimization of NPV subject to regional pressure constraint and average reservoir pressure constraint. The first scenario used unconstrained optimization approach and it produced the highest NPV. However, both $\bar{P}$ and $\bar{P}_r$ were affected. $\bar{P}_r$ was balanced in the second scenario after adding regional pressure constraint to the objective function. $\Delta\bar{P}$ was also maintained in the third scenario after adding average reservoir pressure constraint to the objective function. One important thing to highlight is that NPV got decreased as more constraints were added to the objective function. However, the third scenario which combines all the constraints resulted in the optimum well locations which have high NPV and low $\Delta\bar{P}_r$ and $\Delta\bar{P}$. As mentioned earlier, the constrained optimization approach does not provide single optimal solution. Having all the constraints in the problem, the optimization results in an equation of weighted constraints in which an importance of each constraint can be controlled. Therefore, a wider range of alternative solutions can be achieved when a constraint optimization methodology is used.

7.2 CONCLUSION

The differential evolution algorithm was applied to find the optimum well placement which has the maximum NPV and balanced regional pressure. The optimization was applied in three cases; the first is to optimize NPV alone, the second case is to optimize NPV subject to regional pressure constraint, while the third case is to optimize NPV subject to regional pressure constraint and average reservoir pressure constraint. All these cases were tested on two synthetic models: a channeled reservoir and a reservoir with fully distributed permeability. In each case, regional pressure difference and reservoir pressure drop were compared with those of base cases which have pre-defined well locations. The results proved the success of the proposed approach which finds the optimum well locations which have the maximum NPV with balanced regional pressure and average reservoir pressure. The results of this approach show the effect of subjecting NPV to several constraints and prove how better solutions can be achieved.

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